PREFERENCES FOR ENVIRONMENTAL QUALITY UNDER UNCERTAINTY AND THE VALUE OF PRECISION NITROGEN APPLICATION

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PREFERENCES FOR ENVIRONMENTAL QUALITY

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TABLE OF CONTENTS

LIST OF TABLES

Table Page

Table Page

Table Page

LIST OF FIGURES

Figure Page

NOMENCLATURE

ER	nitrogen application rate historically recommended by the Oklahoma Cooperative Extension Service (90 kg N ha^{-1})
LRP	linear response-plateau
MNL	multinomial logit
NDVI	normalized difference vegetation index
NFOA	nitrogen fertilizer optimization algorithm
N	nitrogen
NH_3	anhydrous ammonia
NRS	nitrogen-rich strip
NRSD	deterministic nitrogen needs predictor based on the nitrogen-rich strip
NRSU	stochastic nitrogen needs predictor based on the nitrogen-rich strip
NUE	nitrogen-use efficiency
ORI	optical reflectance imaging
PPD	deterministic perfect predictor of actual nitrogen needs based on yield data
PPU	stochastic perfect predictor of actual nitrogen needs based on yield data

RS	ramped strip
RSD	deterministic nitrogen needs predictor based on ramped strip
RSU	stochastic nitrogen needs predictor based on ramped strip
UAN	urea-ammonium nitrate solution
WTP	willingness-to-pay

CHAPTER I

PREDICTION UNCERTAINTY AND THE VALUE OF INCREASINGLY SPATIALLY PRECISE NITROGEN NEEDS INFORMATION

Abstract

Nitrogen fertilizer is intensively used in crop agriculture in the United States, and many researchers embrace the goal of improving nitrogen-use efficiency—that is, increasing the proportion of nitrogen fertilizer that is actually used by the crop. This goal can be achieved by applying nitrogen fertilizer to match plant needs as they vary over both time and space. Several different precision agriculture systems have been designed to address this variability of nitrogen needs. Among these innovations are two whole-field systems that use midseason normalized difference vegetation index (NDVI) measures from growing winter wheat to predict the amount of nitrogen the plants require to reach their plateau yield. The nitrogen fertilizer optimization algorithm (NFOA) uses NDVI data from a nitrogen-rich strip and a check strip in the same field to determine the rate at which the crop will cease to be responsive to nitrogen. The ramped strip system applies incrementally increasing nitrogen rates in a strip of plots just after planting, and then collects midseason NDVI readings to determine the rate at which crop response ceases.

This paper is comprised of two sub-papers, the first of which uses datasets from actual ramped strips from on-farm trials. The data used are the outputs from the program

Ramp Analyzer 1.2, and include ramped strip recommendations, as well as NFOA recommendations based on these ramped strips. These data are used to determine whether the ramped strip and NFOA recommendations are precise enough to detect spatial variability of nitrogen needs within fields, among fields and among different counties within the state. The results show that the ramped strip recommendation is a noisy measure of nitrogen needs—perhaps too noisy to be unambiguously profitable.

The second sub-paper uses data from trials at ten experiment station sites throughout the state of Oklahoma. Different preplant nitrogen treatments were applied to replicated plots at these locations between 1998 and 2008, and midseason NDVI and yield data were collected from each plot. These data are used to estimate response of both NDVI and yield to preplant nitrogen as a linear response-plateau. Because the relationship between NDVI and yield is estimated with uncertainty and because the linear response-plateau functional form is nonlinear in parameters, a new methodology is developed using Monte Carlo simulation to predict optimal topdress nitrogen rates based on the NDVI data. This sub-paper also determines whether it is necessary to sample NDVI measures from each field, and how much precision—and profit—would be lost by moving from site-specific (or field-specific) NDVI sampling to region-level sampling. It is determined that the NDVI-based nitrogen needs predictors developed in this paper are imprecise, with the result that profits from region-level sampling and field-level sampling are statistically indistinguishable. Furthermore, it is found that the region- and field-based sampling systems are no better than break-even with the historical extension advice to apply preplant anhydrous ammonia at 90 kg ha^{-1}.

Introduction

Crop agriculture in the United States and other developed nations intensively uses nitrogen fertilizer (N) to increase yields. Expenditures on N account for 28% and 32% of operating expenses for U.S. producers of wheat and corn, respectively (United States Department of Agriculture, 2005). Many researchers have focused on improving N-use efficiency (NUE) in agriculture (e.g., Raun and Johnson, 1999; Greenhalgh and Faeth, 2001; Cassman et al., 1998). Raun and Johnson (1999) find that only 33% of N applied to cereal crops worldwide is recovered in grain. Traditionally, N has been applied prior to planting at a uniform rate selected to meet a yield goal based on historical yields. However, Solie, Raun and Stone (1999) show that natural soil N content (inversely related to crop requirements for N application) varies significantly at a spatial scale of approximately 1 m^2. Additionally, many studies (e.g., Lobell et al., 2005; Mamo et al., 2003; Washmon et al., 2002) find that crop response to N varies within and between fields over time. In other words, potential yield and N requirements vary temporally and spatially within and between fields. This variability results from weather, topology, and their combined effects on N deposition, mineralization, and volatilization. Precision agriculture focuses on providing information to reduce uncertainty about N needs so producers can improve profit margins by avoiding under- or over-application of N.

One innovation in precision agriculture is the sensor-based nitrogen fertilizer optimization algorithm (NFOA) developed by Raun et al. (2002, 2005). The NFOA uses midseason measures of normalized difference vegetation index (NDVI) from growing plants in a non-limiting, nitrogen-rich strip (NRS) to predict the midseason, topdress N application rate required by the crop. Additionally, Raun et al. (2008) have developed a ramped strip (RS) technology to predict optimal N application rates for crops including corn and wheat. This practice involves applying N at incrementally increasing rates to plots arranged in a strip. Such strips can be used to predict, either by visual inspection or by using an optical reflectance sensor, the midseason, topdress N application rate at which crop response to N will cease. The goal of these technologies is to improve NUE—or reduce loss of N inputs to volatilization and runoff—without decreasing yields, so as to improve producer profits. More than one RS or NRS may be used in a single field, but it is recommended that producers place at least one strip in each field each year (Arnall, Edwards and Godsey, 2008). However, is it likely two fields “very close” to each other have similar N requirements? Or what about three such fields? In other words, what is the optimal spatial scale at which to sample NDVI data from experimental strips? Should fields be divided into management zones with a strip in each zone? Is one strip per field sufficient? Or perhaps several strips spread throughout a county could provide an accurate enough prediction for all fields within the county. A county-wide system would be especially valuable to producers who grow wheat for both grain and grazing, for whom establishing an experimental strip might be prohibitively costly due to new fencing costs. The answers to questions about the optimal spatial scale of sampling also will be affected by the strength of the relationship between yields and the NDVI data used to predict them. Despite reduction in uncertainty about spatial and temporal variability of crop response, uncertainty remains an issue for the NFOA and RS technologies as a result of prediction error.

Babcock (1992) suggests that uncertainty results in the historic producer habit of “over-applying” N at a uniform rate every year. He proposes chronic over-application indicates that producers assume crop response to N follows a linear response-plateau (LRP) functional form in which the plateau is uncertain. Tembo et al. (2008) similarly address uncertainty about plateau yields among fields and years. They develop an analytical formula to determine the optimal application rate given inter-annual or inter-field variability of plateau yields. Both Babcock (1992) and Tembo et al. (2008) show that the expected profit maximizing strategy given uncertainty about plateau yields is to apply more N than the deterministic solution suggests. Therefore, inclusion of uncertainty—especially prediction error in the relationship between NDVI and yields—may be essential to accurately predicting the expected profit maximizing midseason, topdress N application rate using the NFOA or RS. This means that prediction error in the predicted intercept and slope should be addressed in addition to plateau uncertainty to improve N requirement prediction.

The remainder of this paper (following the theory section) is divided into two sub-papers, which use different datasets to explore sets of related questions about spatial variability of N requirements. The objectives of the first section are 1a) to determine whether N requirements as predicted by the RS and the NFOA vary by county within a single year and 2a) to determine how consistent (or repeatable) NFOA and RS predictions are over time and space. The objectives of the second section are 1b) to determine whether average plant N requirements for a large region vary by year, 2b) to develop a new process for including prediction error in the RS predictor and 3b) to estimate the relative profitability of four different systems for choosing N application rates. These systems are:

a) a perfect predictor system that uses yield data directly to determine the expected profit maximizing topdress N application rate;

b) the historical recommendation of 90 kg N ha^{-1} as preplant anhydrous ammonia (NH_3);

c) a site-year-specific, NDVI-based predictor of topdress N requirements based on the process developed in objective (2b) above; and

d) a region-year-specific, NDVI-based predictor of topdress N requirements based on the process developed in objective (2b) above.

The results will determine whether annual collection of state- or county-level NDVI data—and subsequent dissemination of N recommendations based on these data—has potential value for winter wheat producers in Oklahoma. Such regional N recommendations, if accurate, might be especially beneficial to those who produce wheat for both grazing and grain, who would likely find the cost of fencing off an experimental strip in each field prohibitive. Notably, using a region-based system would entail more uncertainty about N requirements at any particular site. However, rather than seeking to *reduce* uncertainty in N requirements predictions, this work seeks to account for remaining uncertainty in the predictors, and thereby to reduce the *cost* of prediction error.

Theory

Prior research indicates that output is a function of the most limiting input (e.g., Paris and Knapp, 1989; Berck and Helfand, 1990; Paris, 1992; Chambers and Lichtenberg, 1996; Berck, Geoghegan, and Stohs, 2000; Monod et al., 2002). This functional form is known as a linear response-plateau (LRP). Here, the most limiting input is assumed to be either

N or an unspecified input that is represented as a plateau level of output. However, variables determining the intercept and plateau yields—such as N deposition, mineralization and volatilization—are not known in advance at any given site in any particular year (Mamo et al., 2003). Thus, producers face substantial uncertainty in choosing N application rates. Midseason collection of NDVI data from each site each year can reduce uncertainty caused by spatial and temporal variability. However, predicting yields based on NDVI introduces prediction error that has not yet been addressed in the NFOA or RS methods. The following brief example illustrates how prediction error about the plateau (and only the plateau) affects the process of expected profit maximization.

Brief Example: Expected Profit Maximization when the Plateau

Yield Is Predicted with Error

Suppose a LRP function of expected yield response to N has been predicted for a single site-year based on NDVI data from a RS. For ease of exposition, assume that all parameters besides the plateau are predicted without error—an admittedly unrealistic assumption. Figure I-1 illustrates the hypothetical LRP function. Figure I-2 illustrates the resulting profit function. These two figures show that, when the plateau yield is known with certainty, the profit maximizing N application rate is 30 kg ha^{-1}. Observe the slope of the profit function before and after the optimal rate to see that under-application is relatively more costly than over-applying by the same amount due to the relative prices of N and wheat. However, because the plateau yield is predicted with error, the costs of under- or over-applying are not guaranteed—i.e., there is some *probability* that applying

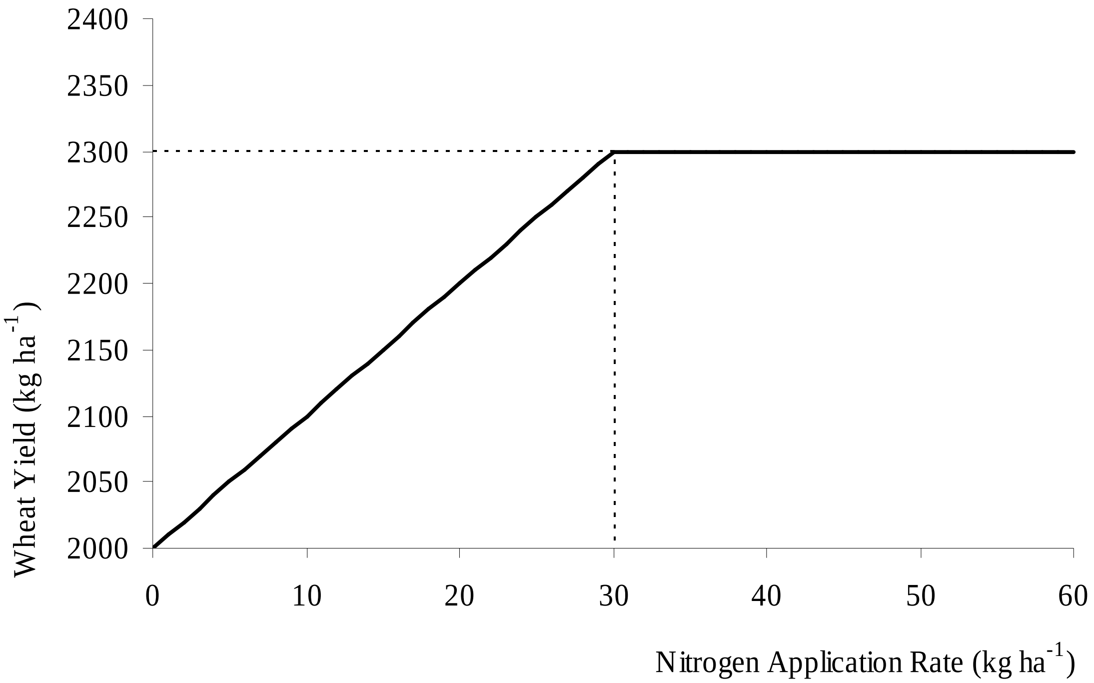

Figure I-1. Yield as a linear response-plateau function of nitrogen application.

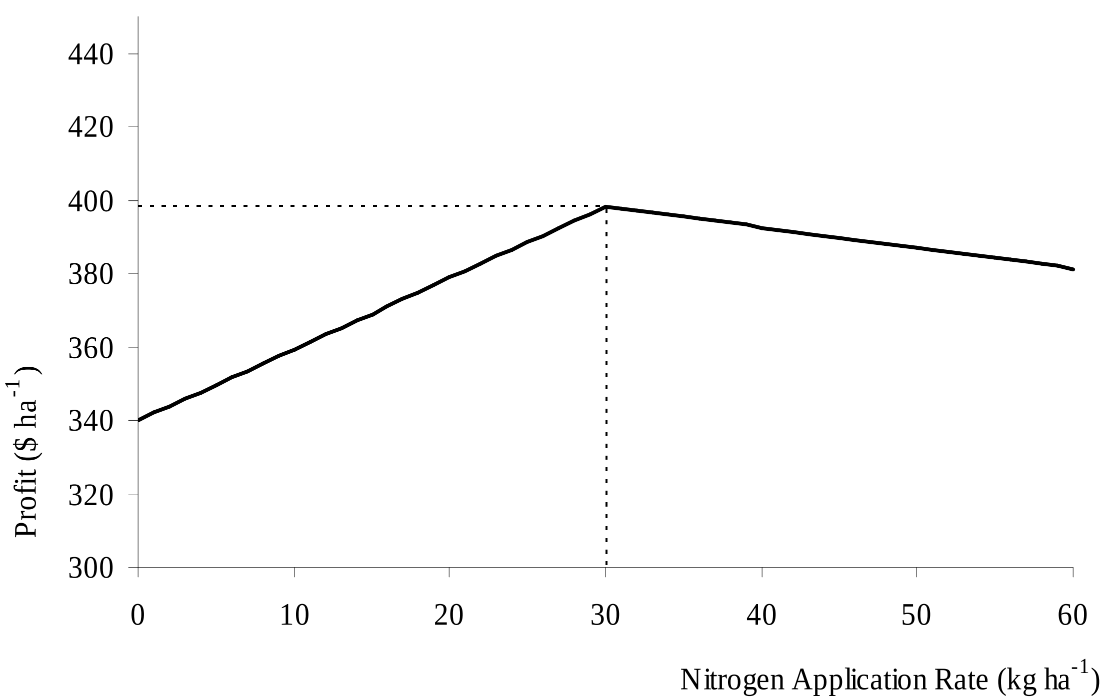

Figure I-2. Profit as a function of nitrogen application.

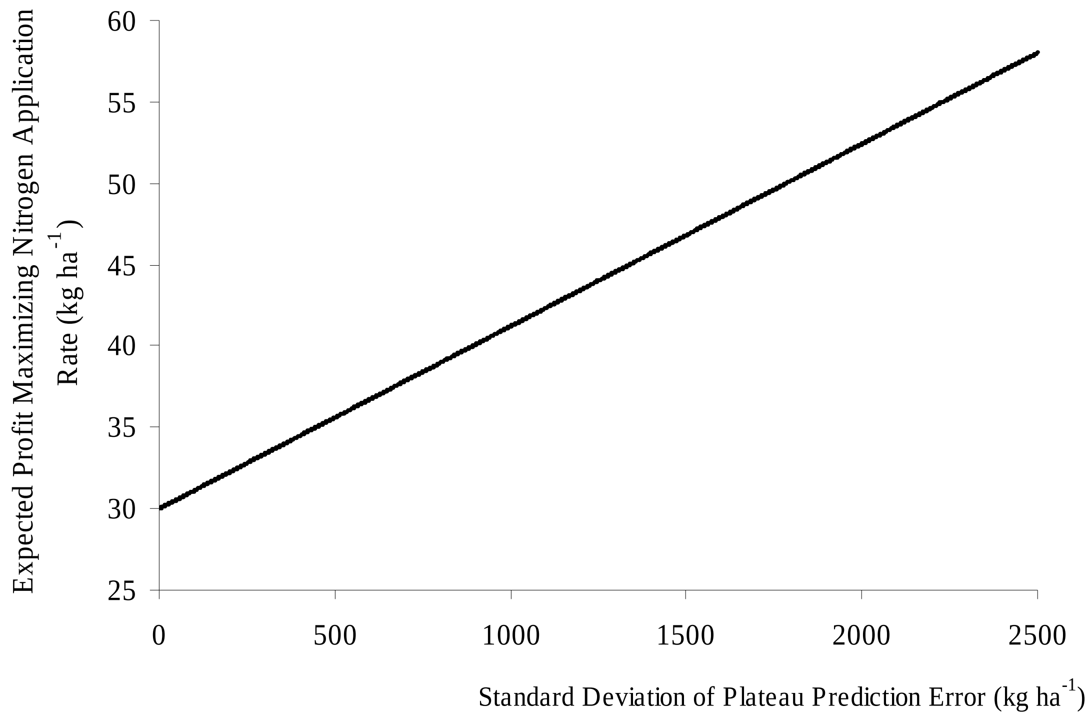

Figure I-3. Expected profit maximizing nitrogen application rate vs. standard deviation of the plateau prediction error.

an additional kg of N will increase profits, and some probability that it will only increase costs. The rate that maximizes *expected* profit is that at which the probability the crop will use the last kg of N applied is the price of N divided by the price of wheat. This fulfils the necessary condition that expected marginal revenue must equal marginal cost for an expected profit maximum. The N application rate at which this condition is met depends upon the variability of the plateau. In this case, it depends on the prediction error in the plateau parameter.

Figure I-3 shows the schedule of expected profit maximizing N application rates for varying levels of uncertainty about the plateau based on equation (14) in Tembo et al. (2008). As prediction error in the plateau parameter increases, higher N application rates are required to satisfy the necessary condition that expected marginal revenue equals marginal cost. Note again that this example treats *only* the error in the predictive relationship between NDVI data and the yield plateau, assuming the other parameters are known with certainty. Prediction error in the intercept, slope and plateau parameters of predicted yield LRP functions will be jointly addressed by Monte Carlo simulation in the procedures section, but consideration of these prediction errors is not conducive to graphical analysis.

The Producer's Decision Problem: Choosing the Expected

Profit Nitrogen Application System

A producer's decision problem is to maximize expected profit under uncertainty (from several sources) by choosing an N recommendation system. This problem can be written as:

(1) $$\max_k E[\pi_k(y(N_k)|N_k = F_k(\phi_k))],$$

where π_k is profit from system *k*; y is yield; N_k is the nitrogen rate recommended by system *k*; ϕ_k is the information set used by system *k* in making an N requirement prediction; and F_k is the function used by system *k* to make a prediction based on ϕ_k. An expected profit maximizing producer will abandon information set ϕ_1 and adopt information set ϕ_2 only if:

(2) $$E[\pi_1(y(N_1)|N_1 = F_1(\phi_1))] < E[\pi_2(y(N_2)|N_2 = F_2(\phi_2))].$$

For example, imagine that information set ϕ_1 provides a more accurate prediction of N needs than information set ϕ_2, helping the producer to reduce N costs from over-application, but that it provides this increased accuracy at a cost that exceeds the expected

N savings. In this case, the producer expects more profit from a less accurate predictor due to the high cost of information, and will switch from ϕ_1 to ϕ_2. Thus, improved prediction accuracy attained by using field-specific information rather than region-specific information must be sufficient to offset the cost of the more spatially precise information. In the case of NDVI-based predictors, prediction error will be determined by multiple factors, including the strength of the relationship between midseason NDVI data and yield, measurement and sampling error in collecting the NDVI measures, as well as the spatial scale of the data collected. So the questions arise: How do crop N requirements vary among fields? Do they vary among regions? Are they predictable using NDVI data?

How Do Nitrogen Needs Vary Spatially, and What Are the Implications?

That Crop N requirements vary temporally and spatially is well established (Lobell et al., 2005; Mamo et al., 2003; Washmon et al., 2002). Both spatial and annual variability in N requirements are related to weather and climate. If spatial variability of N requirements is detectable for different regions (counties, say) within a state, knowledge of this variability could allow somewhat accurate prediction of N requirements for fields within the region. Accounting for both spatial and temporal effects, crop N response is assumed to follow the form:

(3) $$y_{pit} = \min(\beta_0 + \beta_1 N_{pit} + v_i + \varepsilon_t, P + v_i + \omega_i + \varepsilon_t + \upsilon_t) + u_{pit} ,$$

where y_{pit} is the yield on plot *p* in field *i* in year *t*; N_{pit} is the N application rate on plot *p* of field *i* in year *t*; β_0 and P are the estimated intercept and yield plateau, respectively; β_1 is the slope of N response; v_i and ω_i are random effects for field, shifting the intercept and plateau, respectively; ε_t and υ_t are random effects for year, also shifting the intercept and plateau, respectively; u_{pit} is a random disturbance from the mean; and v_i, ω_i, ε_t, υ_t, and u_{pit} are all independent and normally distributed with means of zero and variances σ_v^2, σ_ω^2, σ_ε^2, σ_υ^2, and σ_u^2, respectively. When the true parameters of equation (3) are known, the uniform profit maximizing N requirement for field *i* in year *t* (N_{it}) can be expressed as follows:

$$(4)\quad N_{it} = \begin{cases} (P+\omega_i+\upsilon_t-\beta_0)/\beta_1, & \text{if } p_c(P+\omega_i+\upsilon_t-\beta_0) > (P+\omega_i+\upsilon_t-\beta_0)/\beta_1 - p_a \\ 0, & \text{otherwise,} \end{cases}$$

here p_c and p_a are the price of the crop and the cost of applying N, respectively, and the remaining symbols are previously defined. Because P, β_0 and β_1 are constant, the only parameters changing N requirement from one site-year to another are ω_i and υ_t.

If annual effects (υ_t) on N requirements within a region are significant and large, and if they can be predicted based on some information set—NDVI from RSs at experiment stations, say—producers may find a regional prediction of this annual effect valuable. If the annual effects are large relative to field-specific effects (ω_i) on N requirements, a field-specific information set may not significantly improve producer profit relative to a regional information set. Thus regional predictions of N requirements might be preferable.

Sub-Paper 1: Spatial Variability, Repeatability and Noise in Predictions Made by the Nitrogen Fertilizer Optimization Algorithm and the Ramped Strip

Data

The first dataset used (hereafter called “county-level data”) is comprised of on-farm trials conducted in 2007. This dataset contains 268 observations from on-farm trials of RSs in 15 counties in Oklahoma. Each observation includes the county in which the trial was located, a RS recommendation, a NFOA recommendation, the predicted yield intercept and plateau from the NFOA, and amounts of N actually applied by the producer prior to planting. The exact location of each strip within the county was not recorded. Table I-1 gives the number of observations, mean RS recommendation, mean NFOA recommendation, and the mean predicted yield intercept and plateau from the NFOA by county. All of these measures are outputs of the program Ramp Analyzer 1.2 that fits a linear response-plateau function to the NDVI data to determine the N requirements if N is to be applied at the Feekes 5 growth stage (Raun et al., 2008). The N recommendations in this dataset are used to determine whether the recommendations of the NFOA and RS technologies predict any consistent variability in N requirements among counties. Also, total rainfall data by county are provided from Oklahoma Mesonet stations in or near each county. Rainfall is low for some counties (lowest is 58.29 cm) and high for other counties (highest is 150.80 cm)

The second dataset (hereafter called “field-level data”) contains observations from nine on-farm RS trials conducted in Canadian County in 2008. To create these data, two pairs of RSs were applied in each field as topdress urea-ammonium nitrate solution

Table I-1. Number of Observations, Mean Ramped Strip Nitrogen Recommendation, Mean Nitrogen Recommendations, and Mean Predicted Plateau Yield by County for Dataset Two

County	Trials	RS Rate (kg ha^{-1})	NFOA Rate (kg ha^{-1})	NFOA Intercept (kg ha^{-1})	NFOA Plateau (kg ha^{-1})	Total Rainfall (cm)
Blaine	10	24.53***[a]	-[c]	-[c]	3448.70***	132.23
		(6.01)[b]			(125.87)	
Canadian	44	66.18***	21.51***	2781.62***	3395.95***	135.94
		(7.19)	(2.23)	(71.76)	(91.94)	
Ellis	5	22.62*	5.38**	1710.91***	1837.25***	58.29
		(8.81)	(1.64)	(154.12)	(150.71)	
Grant	20	47.77***	22.68***	2893.63***	3648.15***	103.73
		(6.76)	(3.80)	(190.74)	(209.50)	
Greer	3	45.17**	15.68*	1870.40**	2273.60**	77.13***[d]
		(7.71)	(3.88)	(266.96)	(358.34)	(6.42)
Jackson	6	64.49**	22.40**	2619.68***	3178.00***	55.35
		(21.51)	(6.16)	(130.69)	(246.80)	
Kingfisher	2	83.44	23.52	2701.44	3944.64***	146.46
		(22.96)	(5.60)	(739.20)	(60.48)	
Muskogee	83	60.75***	26.21***	2925.95***	3599.05***	121.87
		(4.77)	(2.50)	(70.85)	(92.96)	
Noble	19	67.61***	24.93***	2639.90***	3355.76***	150.80
		(11.18)	(3.04)	(140.87)	(152.51)	
Nowata	15	58.54***	29.27***	3084.93***	4271.23***	108.43
		(6.54)	(3.59)	(102.25)	(133.21)	
Okmulgee	5	60.70***	17.47**	2870.52***	3316.45***	112.70***[e]
		(7.12)	(4.05)	(162.74)	(241.04)	(27.84)
Ottowa	33	63.57***	26.57***	2643.20***	3322.53***	121.92
		(4.78)	(2.43)	(59.50)	(74.31)	
Pawnee	10	77.62***	35.39***	2461.54***	3423.84***	135.08
		(20.43)	(5.54)	(136.95)	(202.78)	
Payne	5	88.48***	40.77*	3240.38***	4359.94***	137.03***[f]
		(7.10)	(16.61)	(352.27)	(262.83)	(4.89)
Wagoner	8	66.36***	25.06***	2872.80***	3492.30***	111.89
		(15.49)	(3.77)	(112.59)	(175.43)	

[a] One, two or three asterisks indicate statistical significance at the 0.10, 0.05 or 0.01 levels, respectively. The null hypothesis is that the means are zero.
[b] Numbers in parentheses are standard errors.
[c] This variable is not available for observations in Blaine County.
[d] This is the average measure from the three closest Mesonet stations.
[e] This is the average measure from the two Mesonet stations in Okmulgee County.
[f] This is the average measure from the three Mesonet stations in Payne County.

(UAN) after plant emergence. Paired strips were made by making two adjacent passes over the field with the RS applicator, so that the rates in the paired strips increase in opposite directions. Each of the four strips was analyzed with a hand-held Greenseeker optical sensor three times during the growing season, so three RS recommendations, three NFOA recommendations, and three yield plateaus and intercepts predicted by the NFOA are available from each strip. It should be noted that in this dataset (but not in the county-level data) the predicted yield plateaus from the NFOA are right censored at 6048 kg ha^{-1} (90 bu ac^{-1}) even when the predicted intercept is above this level. Such censoring may mean that the NFOA predicts no N response even when the raw NDVI data clearly show N response. Table I-2 lists the planting dates and sensing dates for each field. The amount of N applied by producers prior to sensing was not recorded. These data are used to determine how repeatable NFOA and RS recommendations are over space and through time within fields as a measure of how much noise is present in the predictions.

Procedures

The important question of whether the NFOA and RS recommended N application rates vary by county within a single year is addressed using the county-level data. If different counties have significantly different N requirements, and if these can be predicted by the RS or NFOA, a regional N requirement prediction system based on NDVI may have predictive value. To test for county-level effects, the following Tobit model is estimated:

$$(5) \qquad r_{jk} = \begin{cases} \alpha + \beta N_{jk} + \sum_{k=1}^{K-1} \delta_k D_k & \text{if } r_{jk}^* = \alpha + \beta N_{jk} + \sum_{k=1}^{K-1} \delta_k D_k + \mu_{jk} > 0 \\ 0 & \text{if } r_{jk}^* = \alpha + \beta N_{jk} + \sum_{k=1}^{K-1} \delta_k D_k + \mu_{jk} \le 0 \end{cases}$$

Table I-2. Planting Date and Sensing Dates for Each Field in Dataset Three

Field	Planting Date	Sensing Dates
AC	11/6/2007	01/31/2008
AM	10/10/2007	02/01/2008
		02/19/2008
		03/11/2008
DE	10/14/2007	01/31/2008
		02/19/2008
		03/11/2008
JL	10/12/2007	01/31/2008
		02/20/2008
		03/11/2008
KM	10/5/2007	01/31/2008
		02/19/2008
		03/11/2008
LZ	10/9/2007	01/23/2008
		01/31/2008
		02/19/2008
RZ	10/12/2007	02/04/2008
		02/19/2008
		03/11/2008
SN	10/12/2007	02/04/2008
		02/20/2008
		03/11/2008
TZ	10/10/2007	01/31/2008
		02/19/2008
		03/11/2008

where r_{jk} is the RS recommendation from strip at site *j* in county *k*; α is the intercept recommendation; β is the effect of preplant N application on the RS recommendation; N_{jk} is the amount of preplant nitrogen applied at site *j* in county *k*; δ_k is a fixed effect affecting the mean N recommendation for county *k*; D_k is an indicator variable equal to one when county is *k*, and zero otherwise; *K* is the number of counties; r^*_{jk} is an index of the crop's predicted "need" for N at site *j* in county *k*; μ_{jk} is a normally distributed random deviation in predicted N requirements at site *j* in county *k*, with mean zero and variance σ_μ^2. Based on this model, a likelihood ratio test is used to test the null hypothesis that county level variation in RS recommendations does not exist (i.e., $\delta_k = 0, \forall\, k$). A *t*-test is used to determine whether preplant application of N has any impact on RS recommendations (whether $\beta = 0$). The estimation is done using PROC QLIM in SAS. The above estimation in equation (5) is repeated using the NFOA recommendations as the dependent variable, and perform the hypothesis tests again to determine whether NFOA recommendations vary by county.

The important questions of repeatability of RS and NFOA recommendations across time and space are addressed using the field-level data. Poor repeatability of these recommendations at the same strip over time, or low correlation between recommendations from two adjacent strips would indicate that the RS or NFOA recommendations are too noisy to be useful in predicting N requirements at the single-field level. Such noise could stem from either measurement error or high spatial variability within the field. To determine whether RS detects significant within-field variability of N requirements, the following no-intercept Tobit model is estimated:

$$(6) \qquad r_{ijt} = \begin{cases} \sum_{j=1}^{J} \delta_j D_j & \text{if } r_{ijt}^* = \sum_{j=1}^{J} \delta_j D_j + \varepsilon_{ijt} > 0 \\ 0 & \text{if } r_{ijt}^* = \sum_{j=1}^{J} \delta_j D_j + \varepsilon_{ijt} \le 0 \end{cases}$$

where r_{ijt} is the predicted optimal N application rate on strip *i* in pair *j* on sensing date *t*; δ_j is a fixed effect for pair *j*; D_j is an indicator variable equal to one for pair *j*, and zero otherwise; r_{ijt}^* is a latent variable representing the level of N (including residual and applied N) the plants in strip *i* in pair *j* on sensing date *t* need to reach the predicted plateau yield; ε_{ijt} is a random error term distributed with mean zero and variance σ_{ε}^{2}; and J is the number of strip pairs.

The first hypothesis tested is that N requirement predictions from the RS do not vary between pairs located within the same field—i.e., $\delta_1 = \delta_2, \delta_3 = \delta_4, \ldots, \delta_{J-1} = \delta_J$. Rejection of this hypothesis would indicate that predicted N requirements from the RS vary consistently by pair within each field. Failure to reject the hypothesis would indicate either 1) that there is little variability of N requirements between locations within a field or 2) that the RS is not precise enough to detect this variability. Next, the model is restricted so that predicted N requirements do not vary by field—i.e., $\delta_j = \delta_y, \forall\ j, y$—to determine whether the RS detects significant variability of N requirements between fields. Equation (6) is then re-estimated using the NFOA predictions as the dependent variable (r_{ijt}) to determine whether the NFOA recommendations vary consistently within and between fields.

Additionally, graphical analyses and correlation coefficients are used to determine the strength and significance of the relationships between both RS and NFOA recommendations from 1) strips in the same pair at the same sensing date, 2) different pairs (mean recommendation) in the same field at the same sensing date, and 3) the same strip at the second and third sensing dates. The second and third sensing dates were chosen because the second date is (usually) closest to Feekes 5—the growth stage at which topdress N is normally applied—and because the third sensing date (usually in March) is closest to harvest, and may therefore be the most accurate. The correlation and plot of the relationship between RS and NFOA recommendations at the same strip for the same sensing date are also provided.

Results

Based on the county-level data, results from equation (5) are presented in table I-3. Here, the predicted optimal topdress application rate (either from the RS or the NFOA) is modeled as a function of 1) the preplant N application rate for the field and 2) the county in which the field is located. Notably, the mean RS recommendation (64.01 kg N ha^{-1}) is more than twice the mean recommendation from the NFOA (31.14 kg N ha^{-1}). The signs of the β coefficients for the RS models are negative, which is expected because higher preplant N applications reduce the need for topdress N. Student's *t*-tests, however, indicate that preplant N application has no statistically significant effect on predicted topdress N requirements from the RS method**—**i.e., the null hypothesis $\beta = 0$ cannot be rejected. On the other hand, the β coefficients for the NFOA models are not only negative but are also statistically significant. Assuming NUE of 32% and 50% for preplant and topdress N, respectively, one kg ha^{-1} of preplant N should reduce the need for topdress N by 0.46 kg ha^{-1}, but the coefficients are much smaller: estimated reductions of topdress needs range from 0.12 to 0.22 kg ha^{-1} per additional kg ha^{-1} of preplant N, depending on the model.

The likelihood ratio statistic to determine whether RS method recommendations vary by county is $LR = -2(991.16 - 998.61) = 14.90$, and is distributed chi-square with 13 degrees of freedom. The chi-square critical statistic at the 0.10 level is 19.81, so the test provides no evidence that RS recommendations vary by county. Similarly, no evidence is found to indicate that NFOA recommendations vary by county. The likelihood ratio statistic for this test is $LR = -2(845.85 - 852.50) = 13.30$, which is also

Table I-3. Ramped Strip and Nitrogen Fertilizer Optimization Algorithm Recommendations as Functions of Farmer-Practice Preplant Nitrogen Rate and County

Parameter	Definition	Ramped Strip Recommendations		Nitrogen Fertilizer Optimization Algorithm Recommendations	
		Unrestricted	Restricted	Unrestricted	Restricted
α	Intercept	71.29***[a]	64.01***	27.18***	31.14***
		(6.61)[b]	(3.69)	(3.34)	(1.86)
β	Effect of Preplant Nitrogen	-0.13	-0.12	-0.18***	-0.22***
		(0.11)	(0.10)	(0.06)	(0.05)
δ_1	Effect for County 2	-37.88**	-	-12.67	-
		(18.79)		(9.48)	
δ_2	Effect for County 3	-17.59*	-	3.91	-
		(9.80)		(4.95)	
δ_3	Effect for County 4	-25.03	-	-9.58	-
		(21.61)		(10.90)	
δ_4	Effect for County 5	6.00	-	-1.04	-
		(16.97)		(8.69)	
δ_5	Effect for County 6	19.45	-	6.68	-
		(26.08)		(13.14)	
δ_6	Effect for County 7	-14.82*	-	6.19	-
		(8.21)		(4.15)	
δ_7	Effect for County 8	-6.88	-	4.95	-
		(10.80)		(5.45)	
δ_8	Effect for County 9	-10.40	-	5.42	-
		(10.90)		(5.50)	
δ_9	Effect for County 10	-8.40	-	-6.61	-
		(17.06)		(8.61)	
δ_{10}	Effect for County 11	-6.58	-	1.71	-
		(9.32)		(4.71)	
δ_{11}	Effect for County 12	9.74	-	13.05**	-
		(12.63)		(6.38)	
δ_{12}	Effect for County 13	17.19	-	13.58	-
		(17.36)		(8.76)	
δ_{13}	Effect for County 14	-2.30	-	1.60	-
		(13.90)		(7.02)	
σ_μ^2	Error Variance	35.89***	37.28***	18.10***	18.73***
		(1.81)	(1.88)	(0.92)	(0.95)
Log Likelihood		-991.16	-998.61	-845.85	-852.50

Notes: The unrestricted models allow the mean N recommendation to vary by county, while the restricted models estimate a single mean for all counties. Units are kg ha^{-1}.

[a] One, two or three asterisks represent statistical significance at the 0.10, 0.05 or 0.01 confidence levels, respectively.

[b] Numbers in parentheses are standard errors.

[c] No standard error is estimated because the parameter is restricted.

distributed chi-square with 13 degrees of freedom. Thus, neither the NFOA nor the RS predicts any statistically significant variability of N requirements by county. This does not mean, however, that *actual* N requirements do not vary by county, nor does it mean that this variability cannot be predicted using NDVI data—only that it was not predicted by the RS and NFOA methods used in the county-level data from 2007.

The issues of within- and between-field variability of N requirements are addressed using the field-level data, which includes data from nine fields in Canadian county in 2008. These data are used to estimate equation (6), which models the predicted optimal N application rate (from the RS or NFOA) as a function of the set of paired adjacent strips in which the strip is located. The estimated parameters of this equation for the RS are contained in table I-4. The model with pair effects allows the mean predicted N requirement to be unique for each pair of adjacent strips, while the model with field effects is restricted such that pairs in the same field must have the same mean prediction, and the pooled model assumes the same mean N requirement for all strips in the dataset.

To determine whether field affects the N recommendation from the RS, the field effects model is tested against the pooled model using a likelihood ratio test. The test statistic (chi-square with 8 degrees of freedom) is $LR = -2(-479.26 + 473.43) = 11.66$, but the chi-square critical statistic at the 0.10 level is 13.36, so the test provides no evidence of variation in N requirements predicted by the RS among fields. Because variation in N requirements among fields is well documented (see Lobell et al., 2005; Mamo et al., 2003; Washmon et al., 2002), this result likely indicates that the RS technology is not precise enough to detect this variability. The test to determine whether mean N recommendations vary among pairs of adjacent strips compares the model with

Table I-4. Mean Ramped Strip Recommendation, with and without Fixed Effects for Strip Pair and Field

		Model		
Parameter	Definition	Pair Effects	Field Effects[a]	Pooled[b]
δ_1	Fixed effect for	10.08	19.04	35.19***
	pair 1	(21.18)	(16.07)	(3.42)
δ_2	Fixed effect for	28.00	19.04	35.19***
	pair 2	(21.18)	(16.07)	(3.42)
δ_3	Fixed effect for	65.15***	48.91***	35.19***
	pair 3	(12.23)	(9.28)	(3.42)
δ_4	Fixed effect for	32.67	48.91***	35.19***
	pair 4	(12.23) ***	(9.28)	(3.42)
δ_5	Fixed effect for	59.36***	49.75***	35.19***
	pair 5	(12.23)	(9.28)	(3.42)
δ_6	Fixed effect for	40.13***	49.75***	35.19***
	pair 6	(12.23)	(9.28)	(3.42)
δ_7	Fixed effect for	35.47***	23.07**	35.19***
	pair 7	(12.23)	(9.37)	(3.42)
δ_8	Fixed effect for	10.40	23.07**	35.19***
	pair 8	(12.54)	(9.37)	(3.42)
δ_9	Fixed effect for	26.88**	31.08***	35.19***
	pair 9	(12.23)	(9.28)	(3.42)
δ_{10}	Fixed effect for	35.28***	31.08***	35.19***
	pair 10	(12.23)	(9.28)	(3.42)
δ_{11}	Fixed effect for	35.47***	34.91***	35.19***
	pair 11	(12.23)	(9.28)	(3.42)
δ_{12}	Fixed effect for	34.35***	34.91***	35.19***
	pair 12	(12.23)	(9.28)	(3.42)
δ_{13}	Fixed effect for	16.07	18.61**	35.19***
	pair 13	(12.51)	(9.49)	(3.42)
δ_{14}	Fixed effect for	21.72*	18.61***	35.19***
	pair 14	(12.48)	(9.49)	(3.42)
δ_{15}	Fixed effect for	24.64**	33.13***	35.19***
	pair 15	(12.23)	(9.28)	(3.42)
δ_{16}	Fixed effect for	41.63***	33.13***	35.19***
	pair 16	(12.23)	(9.28)	(3.42)

Table I-4. Mean Ramped Strip Recommendation, with and without Fixed Effects for Strip Pair and Field

		Model		
Parameter	Definition	Pair Effects	Field Effects[a]	Pooled[b]
δ_{17}	Fixed effect for pair 17	68.48^{***} (12.33)	47.25^{***} (9.34)	35.19^{***} (3.42)
δ_{18}	Fixed effect for pair 18	26.69^{**} (12.23)	47.25^{***} (9.34)	35.19^{***} (3.42)
σ_{ε}^{2}	Variance of error	29.95^{***} (2.18)	32.15^{***} (2.34)	34.05^{***} (2.48)
Log Likelihood		-466.79	-473.43	-479.26

Note: Units are kg ha^{-1}.
[a] This model is restricted such that $\delta_1 = \delta_2, \delta_3 = \delta_4, \delta_5 = \delta_6, \text{K}\ , \delta_{17} = \delta_{18}$.
[b] This model is restricted such that $\delta_1 = \delta_2 = \delta_3 =, \text{K}\ , = \delta_{18}$.
[c] One, two or three asterisks (*) indicate statistical significance at the 0.10, 0.05 or 0.01 confidence level, respectively.
[d] Numbers in parentheses are standard errors.

pair effects to the pooled mean model. The likelihood ratio statistic, which is distributed chi-square with 17 degrees of freedom, is $LR = -2(-479.26 + 466.79) = 24.94$. Since the likelihood ratio statistic is slightly greater than the critical value—24.77 at the 0.10 confidence level—the test provides some evidence that mean N recommendations vary among pairs of strips in a consistent way. However, because yield data are not provided, nothing can be said about the economic significance of this finding. What is surprising, though, is that the statistical significance is not stronger. The inference is that recommendations from two adjacent strips in a pair selected at random are only slightly more homogeneous than readings from two randomly selected strips from different pairs—perhaps on opposite sides of Canadian county. The fact that RS predictions of N requirements do not show strong spatial correlation within pairs perhaps indicates that the predictions are imprecise. The lack of precision could be caused by measurement error, such as would occur if the person reading the strip walked at an uneven pace while using the handheld sensor. It should also be noted that the pair effects model does not have a significantly better fit than the field effects model. The likelihood ratio statistic is $LR = -2(-473.43 + 466.79) = 13.28$, and is less than 14.68—i.e., the chi-square critical statistic with 9 degrees of freedom at the 0.10 confidence level. This means that the RS detects no within field variability of N requirements.

Table I-5 shows the mean N application rate recommended by the NFOA with and without fixed effects for strip pair and field. The likelihood ratio test for field effects compares the model with field effects to the pooled model. The likelihood ratio statistic is $LR = -2(-358.39 + 301.65) = 113.48$ with 8 degrees of freedom, which exceeds the chi-square critical value of 20.09 at the 0.01 level. The likelihood ratio statistic to determine whether pair effects improve the fit of the model relative to field effects alone is $LR = -2(-301.65 + 292.12) = 19.06$, and is distributed chi-square with 9 degrees of freedom, and is greater than the critical statistic at the 0.10 level (16.92). Thus, the test finds (marginal) evidence that different sets of paired strips within the same field can have significantly different N recommendations—or that recommendations from adjacent strips in the same pair are more homogeneous than two randomly selected strips from different pairs but within the same field. However, the economic significance of this finding is unknown because yield data are unavailable to verify prediction accuracy.

Figures I-4 and I-5 show plots and correlations of the recommendations from strips in the same pair at the same sensing date for the RS and NFOA, respectively. Note that the correlation between RS recommendations from adjacent strips in figure I-4 is

Table I-5. Mean Nitrogen Fertilizer Optimization Algorithm Recommendation, with and without Fixed Effects for Strip Pair and Field

		Model		
Parameter	Definition	Pair Effects	Field Effects[a]	Pooled[b]
δ_1	Fixed effect for pair 1	7.28 (19.12)	10.64 (15.47)	16.11*** (6.24)
δ_2	Fixed effect for pair 2	14.00 (19.12)	10.64 (15.47)	16.11*** (6.24)
δ_3	Fixed effect for pair 3	-156.84 (0.00)	-46.00*** (17.01)	16.11*** (6.24)
δ_4	Fixed effect for pair 4	-30.53* (16.83)	-46.00*** (17.01)	16.11*** (6.24)
δ_5	Fixed effect for pair 5	63.65*** (11.04)	63.00*** (8.93)	16.11*** (6.24)
δ_6	Fixed effect for pair 6	62.35*** (11.04)	63.00*** (8.93)	16.11*** (6.24)
δ_7	Fixed effect for pair 7	-156.84 (0.00)	-186.66 (0.00)	16.11*** (6.24)
δ_8	Fixed effect for pair 8	-156.84 (0.00)	-186.66 (0.00)	16.11*** (6.24)
δ_9	Fixed effect for pair 9	107.71*** (11.04)	81.48*** (8.93)	16.11*** (6.24)
δ_{10}	Fixed effect for pair 10	55.25*** (11.04)	81.48*** (8.93)	16.11*** (6.24)
δ_{11}	Fixed effect for pair 11	43.12*** (11.04)	26.81*** (9.20)	16.11*** (6.24)
δ_{12}	Fixed effect for pair 12	9.86 (12.00)	26.81*** (9.20)	16.11*** (6.24)
δ_{13}	Fixed effect for pair 13	26.74** (11.23)	39.94*** (9.06)	16.11*** (6.24)
δ_{14}	Fixed effect for pair 14	53.94*** (11.15)	39.94*** (9.06)	16.11*** (6.24)
δ_{15}	Fixed effect for pair 15	-29.28* (16.63)	-45.06*** (16.81)	16.11*** (6.24)
δ_{16}	Fixed effect for pair 16	-156.84 (0.00)	-45.06*** (16.81)	16.11*** (6.24)

Table I-5. Mean Nitrogen Fertilizer Optimization Algorithm Recommendation, with and without Fixed Effects for Strip Pair and Field

		Model		
Parameter	Definition	Pair Effects	Field Effects[a]	Pooled[b]
δ_{17}	Fixed effect for pair 17	45.36*** (11.17)	40.42*** (8.99)	16.11*** (6.24)
δ_{18}	Fixed effect for pair 18	36.03*** (11.04)	40.42*** (8.99)	16.11*** (6.24)
σ_{ε}^{2}	Variance of error	27.04*** (2.53)	30.93*** (2.89)	55.42*** (5.56)
Log Likelihood		-292.12	-301.65	-358.39

Note: Units are kg ha^{-1}.
[a] This model is restricted such that $\delta_1 = \delta_2, \delta_3 = \delta_4, \delta_5 = \delta_6, \ldots, \delta_{17} = \delta_{18}$.
[b] This model is restricted such that $\delta_1 = \delta_2 = \delta_3 =, \ldots, = \delta_{18}$.
[c] One, two or three asterisks (*) indicate statistical significance at the 0.10, 0.05 or 0.01 confidence level, respectively.
[d] Numbers in parentheses are standard errors.

slightly negative, though not significant (p = 0.61). This result indicates that the RS is a noisy predictor of N requirements. On the other hand, the correlation between NFOA recommendations from adjacent strips in figure I-5 is 0.56, and is statistically significant (p < 0.01). Figure I-6 shows the mean RS recommendation from one pair of strips plotted against the mean RS recommendation from the other pair of strips in the same field at the same sensing date, while figure I-7 plots the NFOA recommendations in the same manner. The mean RS recommendations from pairs in the same field have low correlation (0.01) that it is not statistically significant (p = 0.98). However, the mean NFOA recommendations from the different pairs are highly (0.74) and significantly correlated (p < 0.01).

Figures I-8 and I-9 show plots of recommendations at the same strip at the second sensing date (usually February) and the third sensing date (usually March) for the RS and

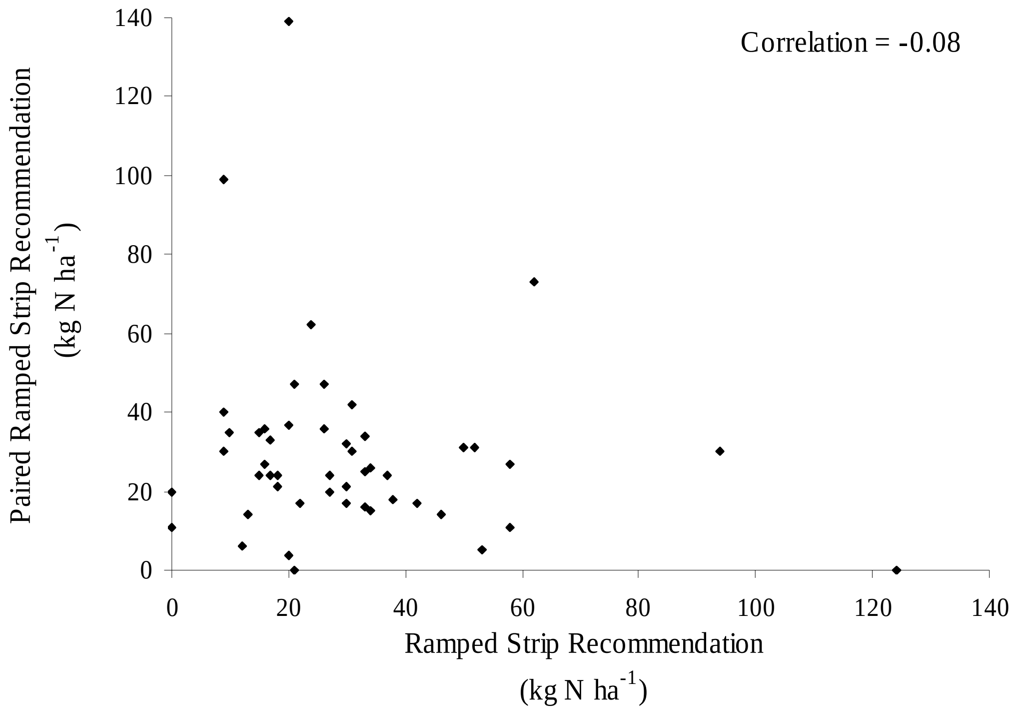

Figure I-4. Ramped strip recommendation at one strip vs. ramped strip recommendation from the other strip in the same pair at the same sensing date.

NFOA, respectively. For the RS measures, the correlation is only 0.10, and is not statistically significant ($p = 0.57$). The correlation for the NFOA recommendations is 0.56, and is significant at the 0.01 confidence level. The plots and correlations in figures I-4 through I-9 indicate that the RS recommendations are not stable over time and space within the same growing season. This result likely indicates that RS recommendations in the field-level data do not very accurately represent actual N requirements. However, the relative spatial and temporal stability of the NFOA recommendations does not necessarily mean that NFOA recommendations are any more accurate than the RS predictions. To explicitly determine whether NFOA predictions are accurate, production

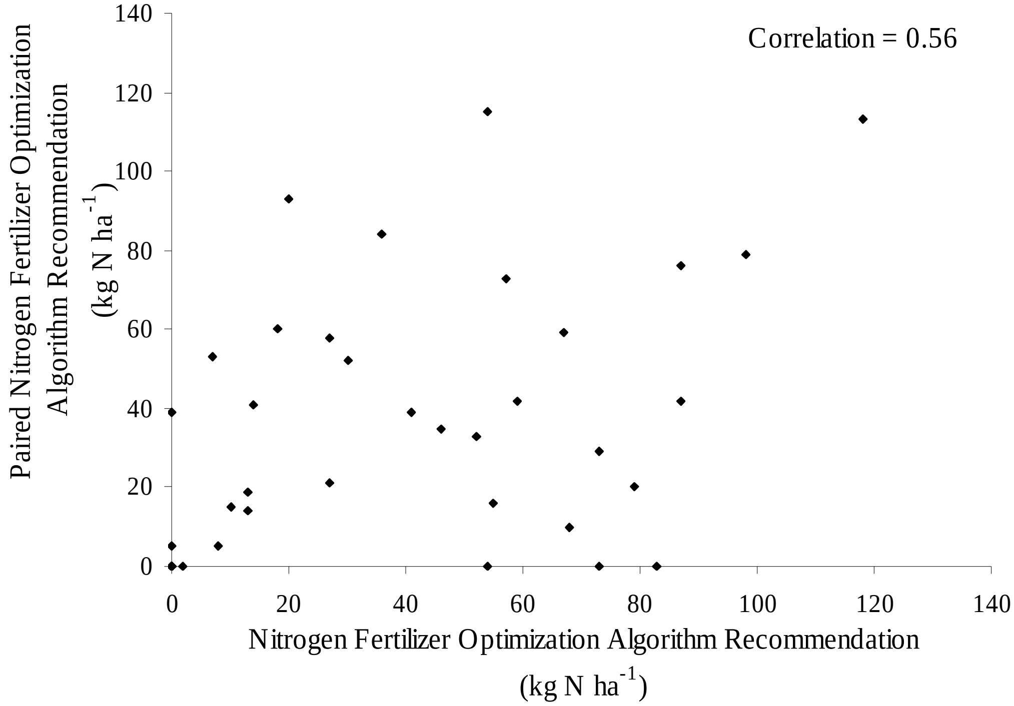

Figure I-5. Nitrogen fertilizer optimization algorithm recommendation at one strip vs. nitrogen fertilizer algorithm recommendation from the other strip in the same pair at the same sensing date.

functions would have to be estimated using yield response data (which were not recorded) from the fields in the field-level dataset.

One reason why the NFOA recommendations show higher spatial relatedness may be the NFOA's propensity to predict optimal rates of zero kg ha^{-1}. The NFOA, as used in the field-level dataset, restricts the predicted plateau yield for each strip to be no greater that 6048 kg ha^{-1}. Thus, in cases where the NFOA predicts a yield intercept greater than 6048 kg ha^{-1} the predicted plateau yield is still no greater than 6048 kg ha^{-1}, without regard to NDVI response to N. However, if NDVI is a noisy predictor of yield—i.e., if the relationship between NDVI data and yields varies among fields or by wheat variety—

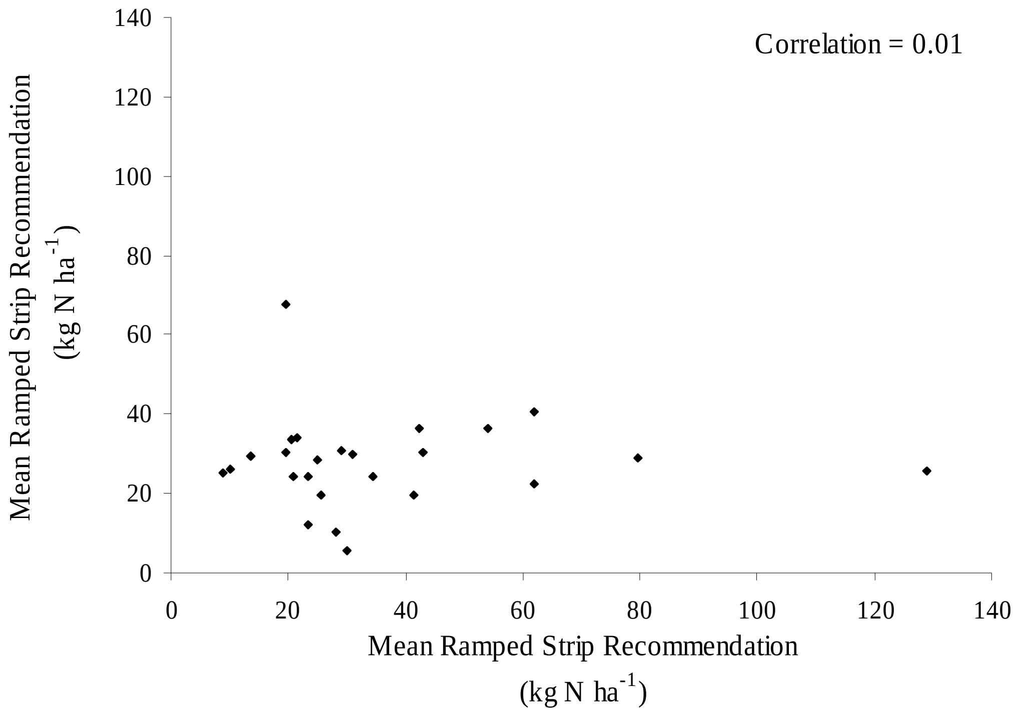

Figure I-6. Mean ramped strip recommendation from one pair of strips vs. mean ramped strip recommendation from the other pair in the same field at the same sensing date.

then imposing this restriction on the plateau yield could bias the NFOA to predict that no N should be applied when, in fact, it would be optimal to apply N in some quantity.

Figure I-10 shows a plot of NFOA recommendations against RS recommendations from the same strip at the same sensing date. Note that the NFOA often recommends no application while the RS recommends some positive application rate (36 of 100 observations). This means that even when NDVI data indicate an N response—i.e., the average NDVI reading at one end of the strip is different from the average NDVI reading at the other end—the NFOA still assumes no N response by assuming that the relationship between NDVI and yields is estimated without error. However, the error

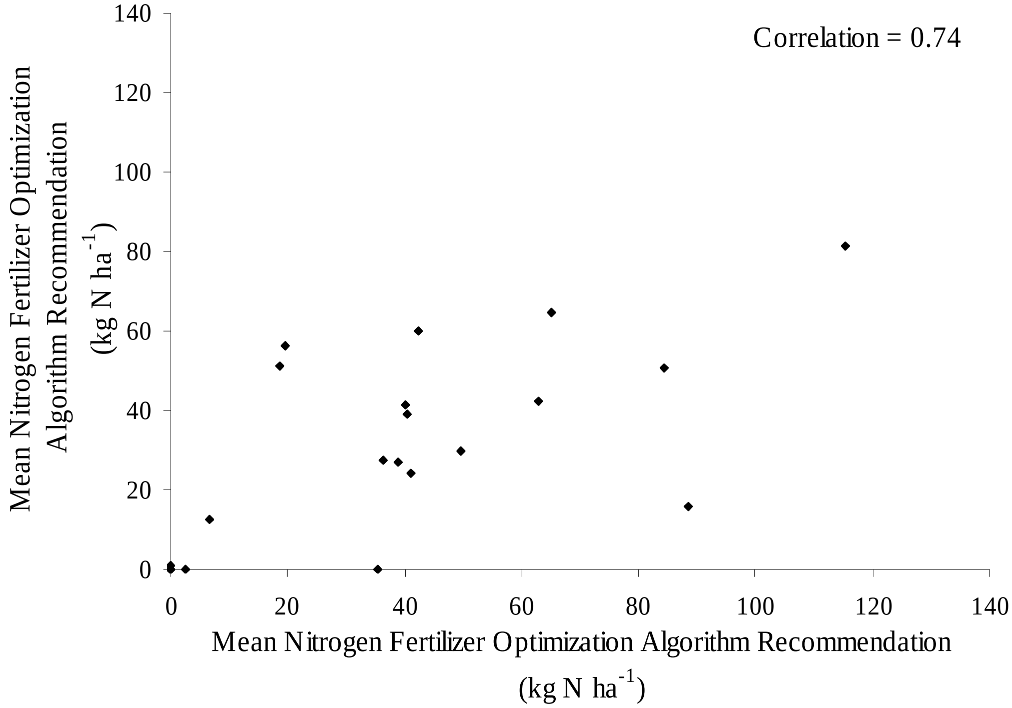

Figure I-7. Mean nitrogen fertilizer optimization algorithm recommendation from one pair of strips vs. mean nitrogen fertilizer optimization algorithm recommendation from the other pair in the same field at the same sensing date.

variance may be large, or may be heteroskedastic such that it increases for higher NDVI readings, or may be unique to each field. Thus, imposing this type of restriction on a plateau predicted with error may bias the NFOA predictions toward zero. Perhaps this problem could be solved by explicitly introducing this error variance into the NFOA.

Conclusions

First and foremost, the results indicate that the RS technique for N requirements prediction in growing winter wheat is likely too noisy to be useful in terms of accurately

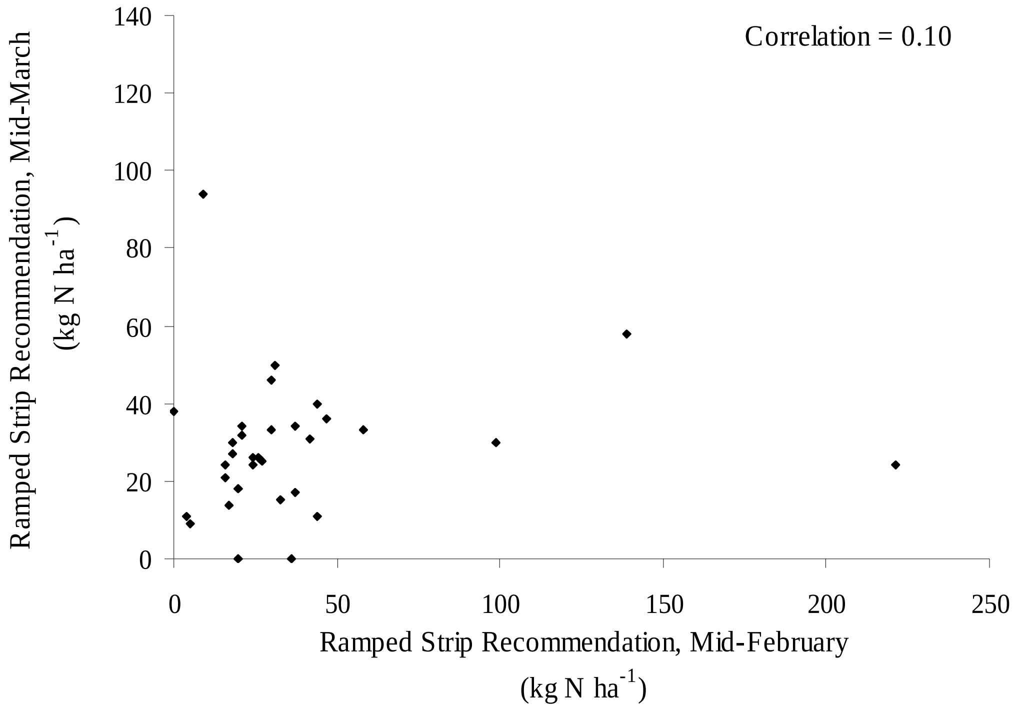

Figure I-8. Ramped strip recommendation from Mi-March vs. ramped strip recommendation from the same strip in Mid-February.

and consistently predicting optimal N application levels. For example, the RS does not detect any significant, consistent variability of N requirements between counties, between fields, or within fields (tables I-3 and I-4, respectively). Furthermore, RS recommendations are neither 1) significantly correlated with RS recommendations from nearby strips (figure I-4) nor steady across sensing dates (figure I-8). These facts together indicate that the RS technology requires continuing development to address the sources of noise that adversely affect the consistency of its predictions.

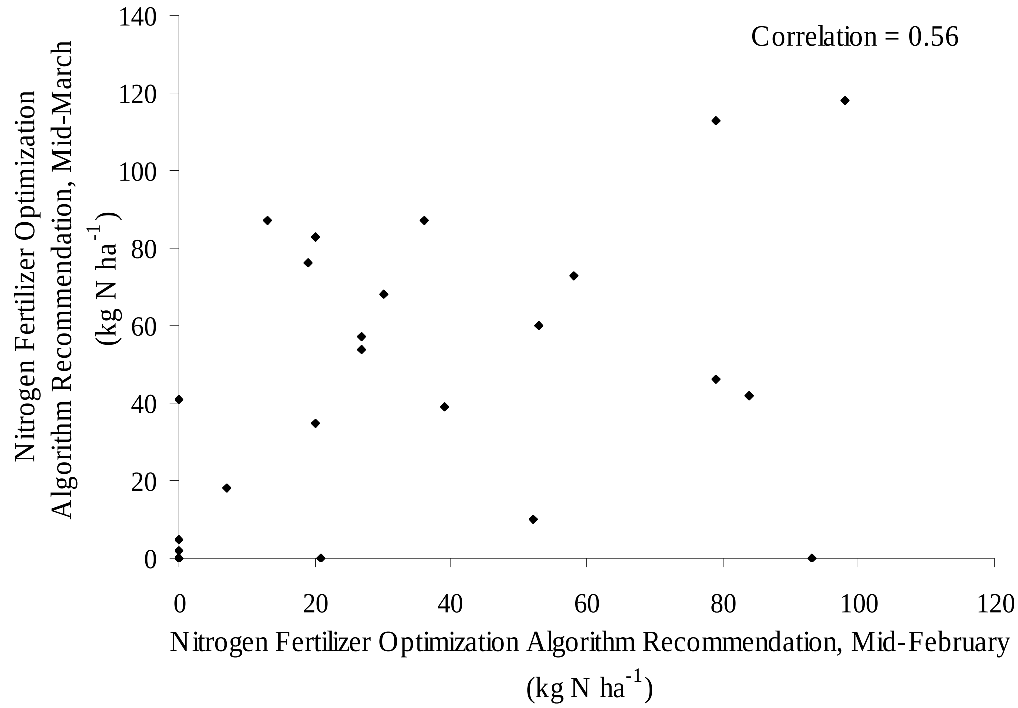

Figure I-9. Nitrogen fertilizer optimization algorithm recommendation from Mid-March vs. nitrogen fertilizer optimization algorithm recommendation from the same strip in Mid-February.

The NFOA recommendations (as opposed to the RS recommendations) seem more consistent with expectations about variability of N requirements between and within fields (table I-5 and associated hypothesis tests). NFOA recommendations are also significantly correlated within pairs (figure I-5), within fields (figure I-7) and across time within the growing season (figure I-9). However, the reason for this high correlation may be the restriction on the plateau yield predicted by the NFOA. Because the plateau and intercept are predicted based on the estimated (with error) relationship between NDVI data and yields, the predictions are uncertain. Because of this estimation error, the NFOA

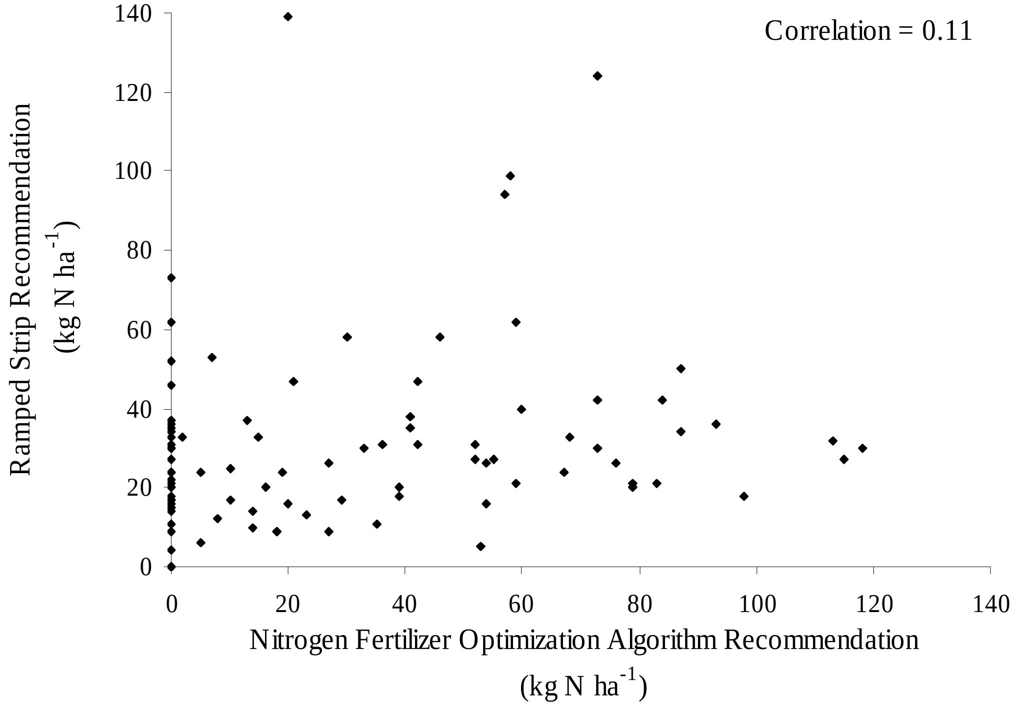

Figure I-10. Ramped strip recommendation vs. nitrogen fertilizer optimization algorithm recommendation from the same strip at the same sensing date.

occasionally predicts crop yields will be unresponsive to N (by capping the predicted yield plateau) even when NDVI data *are* N responsive.

Ultimately, both the NFOA and RS methods used to create these data are too noisy to accurately predict crop N requirements. However, these techniques have been—and continue to be—used by producers (Raun et al., 2008). Producers using the RS and NFOA technologies do so because they believe it is profitable. Perhaps these producers are not using the technology precisely as intended. For example, they may be integrating farmer intuition into the process of choosing an N application rate—using the NFOA or RS in addition to rules of thumb they have always used. It may be optimal to use a combined information set that includes the old (farmer practice) and new (NFOA or RS) decision tools in the choice of N application rates. The results in this paper suggest several potential avenues of related research, including: 1) the creation of a formal Bayesian framework that will allow producers to input a set of field-specific rules of thumb, say, into the NFOA and RS methodologies, 2) the development of a framework for including uncertainty (such as the error variance of the relationship between NDVI and yield) in the NFOA or RS methodologies, 3) use of improved estimation methods for the ramped strip linear response-plateau functions and 4) development of more accurate measurement techniques for collecting NDVI data (as opposed to walking with a handheld sensor. Any of these pursuits (or several jointly) might improve the accuracy of midseason N requirements predictions based on the RS and NFOA.

Sub-Paper 2: Prediction Uncertainty and the Value of Increasingly Spatially Precise Sampling of Optical Reflectance Data

Data

The dataset used in this sub-paper consists of experiments conducted at ten sites throughout the state of Oklahoma between 1998 and 2008. The ten sites are located at the Efaw, Haskell, Hennessey, Lahoma, Lake Carl Blackwell, Perkins, Stillwater, and Tipton agricultural experiment stations. Table I-6 contains the specifics about N treatment levels, replications, soil types, and dates for each location, while the map in figure I-11 shows the locations of the sites. Each site-year had at least three different levels of N treatment, which differed across sites, and occasionally between years at the same location. The number of replications at each N application rate varies by site-year. NDVI measures for

Table I-6. Locations, Years, Soil Types, and Nitrogen Levels, and Replications for Experiments in Dataset One

Experiment Station	Years	Soil Type	Nitrogen Treatment Levels (kg ha^{-1})					
Efaw 1	1999-2006	Easpur loam	0	45	90	179	269	538[a]
			(3)	(3)	(3)	(3)	(3)	(3)[b]
Efaw 2	1999-2003	Easpur loam	0	56	90	123		
			(3)	(6)	(6)	(6)		
Haskell	1999-2002	Taloka silt	0	112	168			
		loam	(8)	(16)	(4)			
Hennessey	2000-2003	Shellabarger	0	56	90	123		
		sandy loam	(3)	(5)	(6)	(6)		
Lahoma	1999-2008	Grant silt	0	22	45	67	90	112
		loam	(8)	(4)	(4)	(4)	(4)	(4)
Lake C.B.	2004, 2006	Port silt loam	0	50	100			
			(4)	(4)	(4)			
Perkins 1[c]	1998-2006	Teller sandy	0	56	112	168		
		loam	(3)	(3)	(3)	(3)		
Perkins 2	1998	Teller sandy	0	56	112	168		
		loam	(9)	(9)	(9)	(9)		
Stillwater	1999-2006,	Norge silt	0	45	90	134[d]		
	2008	loam	(8)	(4)	(4)	(4)		
Tipton	1998	Tipton silt	0	56	112	168		
		loam	(12)	(12)	(12)	(12)		

[a] Rate not available in 2000.
[b] Numbers in parentheses are the number of replications at each rate each year.
[c] Numbers of replications are the same in 1998 as at Perkins 2.
[d] Rate not available in 2004, 2005, 2008.

each observation were collected around Feekes growth stage 5, and yield was measured at harvest. These data are used to 1) determine whether year has a significant impact on N requirements across locations throughout the state of Oklahoma, 2) determine the relationship between NDVI information and the parameters of the LRP functions yield response to N, 3) create a framework for introducing the uncertainty about this relationship into a RS-type N requirements prediction techniques, and 4) estimate the relative profitability of the different N requirement prediction systems described in the introduction.

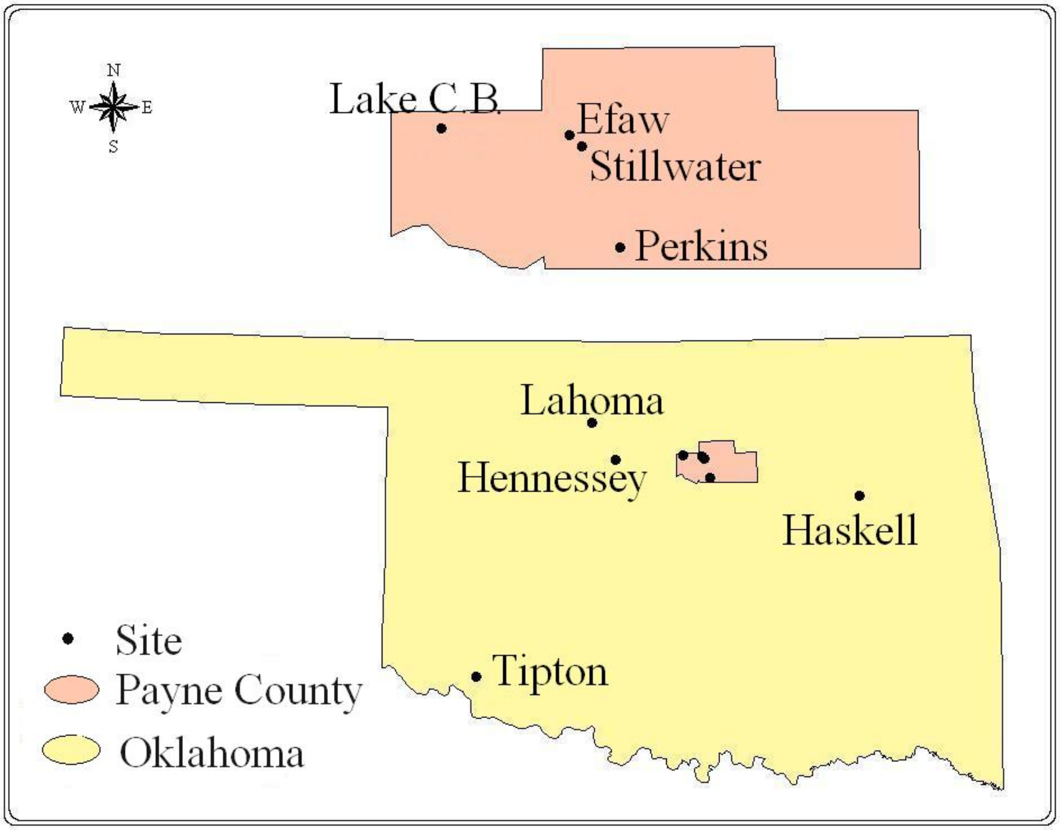

Figure I-11. Map of experimental locations.

Based on local cooperative prices on February 14, 2009, assumed prices of N from UAN and NH_3 are \$1.10 kg^{-1} and \$0.57 kg^{-1}, respectively. Custom application costs for UAN are assumed to be \$9.71 ha^{-1} and custom application of NH_3 is \$20.49 ha^{-1} (Doye, Sahs and Kletke, 2007). The wheat price is \$0.24 kg^{-1}

RS application is assumed to take place early after planting as topdress UAN. Producers are advised to apply as many as 3 strips per field, each measuring 3 m by 55 m (0.0165 ha), starting at an application rate of 0 kg ha^{-1}, and increasing the application rate in increments of 14.56 kg ha^{-1}, until reaching the maximum rate that could possibly be used by the plants (assumed to be 134 kg ha^{-1}). Thus, the average N application rate in the three RSs is 67 kg ha^{-1}. It is also assumed that because the RSs are applied separately

Table I-7. Partial Budget for Creation and Use of Three Ramped Strips in a 63 ha field

Operating Input	Units	Price	Quantity	Cost
UAN	kg	1.10	3.31	3.64
Road Time	km	4.12	8	32.96
Coop Labor	hr	17.50	2.50	43.75
Sensor	ha	1.08	63.00	68.04
Producer Labor	hr	17.50	2.50	43.75
Total Cost of RS	Field			192.14
Total Cost of RS	ha			3.04

from preplant N, the producer pays road time totaling eight km per field at \$4.12 km^{-1} for delivery of the RS applicator. It is assumed that the custom application of the strips takes 2.5 hours of custom labor, and that the producer later spends 2.5 hours reading the three strips with his own Greenseeker® sensor. Thus, the total cost of creating and using three RSs is \$192.14 per field, or \$3.04 ha^{-1} for a 63 ha field on a 1000 ha farm, where the cost of the sensor is spread over the entire farm. Table I-7 is a partial budget for the creation and use of the strips.

Procedures

Variability of Nitrogen Needs by Year and Location

One objective of this sub-paper is to quantify variation in N requirements by year and experimental site. This is of interest because, for a regional N requirement prediction system to be of value, annual effects on N needs within the region must exist and be predictable with some accuracy. Thus, tests for field-specific and year specific effects on N needs are conducted based on the following model:

$$(7) \quad y_{pit} = \min(\beta_0 + \beta_1 N_{pit} + \sum_{i=1}^{N-1} v_i D_i + \varepsilon_t, P + \sum_{i=1}^{N-1} v_i D_i + \sum_{i=1}^{N-1} \omega_i D_i + \varepsilon_t + \upsilon_t) + u_{pit},$$

y_{pit} is yield on plot *p* of field *i* in year *t*; β_0 is the intercept yield; β_1 is the crop N response rate; P is the expected yield plateau; v_i and ω_i are fixed effects for field *i*, shifting the intercept and plateau, respectively; D_i is an indicator variable equal to one for field *i* and zero otherwise; ε_t and υ_t are random effects for year *t*, also shifting the intercept and plateau, respectively; u_{pit} is a random disturbance; and ε_t, υ_t and u_{pit} are from independent normal distributions with means zero and variances σ_ε^2, σ_υ^2, and σ_u^2, respectively. The determination of whether plateau yield shifts randomly (and independently of intercept yield) by year is made using a likelihood ratio test with one degree of freedom to test the restriction $\sigma_\upsilon^2 = 0$. Rejection of this restriction would be evidence that accurate predictions of annual effects could be valuable information to producers making a choice of N application rate in the region for which the prediction was made. The restriction $\omega_1 = \omega_2 =, \ldots, = \omega_{N-1} = 0$ is also tested, where $N-1$ is the number of estimated field-specific plateau fixed effects in the model, to determine whether the mean yield plateau varies by site (at the field-level, say). If this type of variation of plateau yield is found, it will indicate that N requirements also vary by field, which is expected on the basis of the literature (Lobell et al., 2005; Mamo et al., 2003; Washmon et al., 2002).

Defining a Predictive Relationship

This paper develops an N requirements prediction system based on the RS methodology that accounts for two types of uncertainty: 1) estimation uncertainty—or uncertainty about the value of the parameters of NDVI response to N—and 2) prediction uncertainty—or uncertainty in the predictive relationship between NDVI response and yield response to N. To this end, the following equations are estimated for each site-year:

(8) $$y_{it} = \min(\beta_{0t} + \beta_{1t} N_{it}, P_t) + u_{it} \text{ and}$$

(9) $$insey_{it} = \min(\alpha_{0t} + \alpha_{1t} N_{it}, \phi_t) + \eta_{it},$$

where y_{it} is the measured yield on plot *i* in field-year *t*; β_{0t} is the intercept yield for field-year *t*; β_{1t} is the yield response to N in field-year *t*; P_t is the plateau yield in field-year *t*; u_{it} is a normally distributed disturbance with mean zero and variance $\sigma^2_{u\,t}$ for plot *i* in field-year *t*; $insey_{it}$ is the measured NDVI on plot *i* in field-year t; α_{0t} is the NDVI intercept for field-year *t*; α_{1t} is the NDVI response to N for field-year *t*; ϕ_t is the NDVI plateau for field-year *t*; and η_{it} is a normally distributed disturbance with mean zero and variance $\sigma^2_{\eta_t}$ for plot *i* in field-year *t*.

Of paramount interest is the accuracy with which the parameters of equation (8) can be predicted by the parameters of equation (9). In other words, how do the LRP functions of NDVI compare with the LRP functions of actual yields? To answer this question, seemingly unrelated regression is used in SAS PROC MODEL to estimate the following:

(10) $$\hat{\beta}_{0t} = \lambda_0 + \lambda_1 \hat{\alpha}_{0t} + \varepsilon_t$$

(11) $$\hat{\beta}_{1t} = \gamma_0 + \gamma_1 \hat{\alpha}_{1t} + r_t \text{, and}$$

(12) $$\hat{P}_t = \rho_0 + \rho_1 \hat{\phi}_t + e_t,$$

where $\hat{\beta}_{0t}$, $\hat{\beta}_{1t}$ and $\hat{P}_t$ are the estimated parameters of the LRP response of yield to N application from equation (8); $\hat{\alpha}_{0t}$, $\hat{\alpha}_{1t}$ and $\hat{\phi}_t$ are the estimated parameters of the LRP response of NDVI to N application from equation (9); λ_1 and λ_2 are the intercept and slope, respectively, of the relationship between the NDVI intercepts and the yield intercepts; γ_1 and γ_2 are the respective intercept and slope of the relationship between the responses of yield and NDVI to N application; ρ_0 and ρ_1 are the intercept and slope of the relationship between the NDVI plateau and yield plateau; and ε_t, r_t and e_t are random, correlated error terms with means zero and variance-covariance matrix:

(13)
$$\mathbf{\Sigma} = \begin{bmatrix} \boldsymbol{\sigma}_{\varepsilon\varepsilon} & \boldsymbol{\sigma}_{\varepsilon r} & \boldsymbol{\sigma}_{\varepsilon e} \\ \boldsymbol{\sigma}_{\varepsilon r} & \boldsymbol{\sigma}_{rr} & \boldsymbol{\sigma}_{er} \\ \boldsymbol{\sigma}_{\varepsilon e} & \boldsymbol{\sigma}_{er} & \boldsymbol{\sigma}_{ee} \end{bmatrix} \otimes \mathbf{I} = \mathbf{\Sigma}_c \otimes \mathbf{I},$$

where $\boldsymbol{\sigma}_{\varepsilon\varepsilon}$ is the *n* by *n* variance-covariance matrix for equation (10); where $\boldsymbol{\sigma}_{rr}$ is the *n* by *n* variance-covariance matrix for equation (11); where $\boldsymbol{\sigma}_{ee}$ is the *n* by *n* variance-covariance matrix for equation (12); the off-diagonal elements are nonzero cross-model correlation matrices of the contemporaneous error terms, and $\mathbf{I}$ is an *n* by *n* identity matrix. The parameters estimated in equations (8) through (13) are used to determine the optimal N application rates for 1) the field-level perfect predictor, 2) the field-level NDVI-based predictor, and 3) the regional NDVI-based predictor, as well as to calculate the net returns above N-related costs[1] (hereafter simply called “net returns”) for each prediction system.

[1] N-related costs as defined here include 1) the cost of purchasing N, 2) the cost of custom application of N and 3) the cost of any technology and/or experimental strip required any given system for predicting the optimal N application rate.

The Perfect Prediction Nitrogen Rate

The perfect prediction N application rate for each site-year is determined based on the yield data. This rate produces the maximum possible expected profit for a topdress-only N application system. However, because the true parameters of the LRP functions estimated in equation (8) are unknown, and because the LRP functional form is nonlinear in parameters, the true optimal N application rate cannot be calculated deterministically (Babcock, 1992). Babcock (1992) and Tembo et al. (2008), however, do not consider uncertainty in *all* parameters of the LRP functional form—only in the yield plateau. The solution derived here is different, in that it accounts for uncertainty in the intercept, slope *and* plateau parameters. This work also differs from that of the preceding authors by considering parameter estimation uncertainty, rather than uncertainty caused by annual variability of the plateau. To account for estimation uncertainty, ten thousand Monte Carlo observations are used to determine the expected profit maximizing N application rate for each site-year. These simulated observations are obtained by the process:

(14) $$\hat{\boldsymbol{\beta}}_{jt} = \hat{\boldsymbol{\beta}}_t + \mathbf{Q}_t'\mathbf{z}_j \text{ and } \mathbf{Q}_t\mathbf{Q}_t' = \boldsymbol{\Omega}_t ,$$

where $\hat{\boldsymbol{\beta}}_{jt}$ is the j^{th} simulated 4 by 1 vector of LRP parameters for site-year t based on the estimation of equation (8)—i.e., $\hat{\beta}_{0jt}$, $\hat{\beta}_{1jt}$, $\hat{P}_{jt}$, and $\hat{\sigma}^2_{u\,jt}$; $\hat{\boldsymbol{\beta}}_t$ is the 3 by 1 vector of LRP parameter estimates for site-year t from equation (8); $\mathbf{Q}_t'$ is the 3 by 3 lower triangular Cholesky decomposition matrix of $\boldsymbol{\Omega}_t$, which is the 3 by 3 variance-covariance matrix of parameter estimates for site-year t; $\mathbf{z}_j$ is the j^{th} 3 by 1 vector of random deviates from a standard normal distribution; $j = 1, \ldots, J$; and J is ten thousand.

The true (or perfect prediction) application rate that maximizes expected profit for site-year t is then calculated based on the Monte Carlo observations generated in equation (14) using the following maximization problem:

$$(15) \qquad \max_{N_t} E(\pi(N_t)) = \sum_{j=1}^{J} \frac{p_c \max(\min(\hat{\beta}_{0jt} + \hat{\beta}_{1jt} N_t, \hat{P}_{jt}), \hat{\beta}_{0jt})}{J} - p_n N_t - p_a \delta_t ,$$

where π is profit; N_t is the uniform N application rate for site-year t; p_c is the wheat price; $\hat{\beta}_{0jt}$ is the j^{th} simulated intercept coefficient for site-year t; $\hat{\beta}_{1jt}$ is the j^{th} simulated slope coefficient for site-year t; $\hat{P}_{jt}$ is the j^{th} simulated plateau coefficient for site-year t; p_n is the price of N from UAN solution; p_a is the custom application cost for UAN solution; δ_t is an indicator variable equal to one if $N_t > 0$; J is ten thousand; and the max function ensures that yield is always greater than or equal to the intercept yield.

Nitrogen Needs Predictions by Site-Year

Next, the predicted economically optimal N application rate must be predicted for each site-year based on the available NDVI data. The methods use to predict these application rates differ from those of Raun et al. (2008) by accounting for estimation uncertainty about the estimated parameters in equation (9) and of the parameters estimated in equations (10) through (12). To begin the prediction process, ten thousand sets of Monte Carlo simulated parameters are generated for each site-year based on the parameter estimates from equation (9). The process for generating these Monte Carlo simulations is the same as that described in equation (14), and is used (as before) to account for parameter estimation uncertainty. However, these simulated parameters cannot be directly used to predict the expected profit maximizing N application rate because they represent the response of expected NDVI measures (rather than yields) to N application.

To predict the economically optimal N application rate based on these LRP functions of NDVI, the Monte Carlo simulated parameters based on equations (9) and (14) must be converted to expected yield parameters. This transformation is made using the seemingly unrelated regression parameters estimated in equations (10), (11) and (12), where the parameters of the expected yield functions depend on the parameters of the NDVI functions. However, the parameters describing the relationships between the LRP functions of NDVI and yield data are *also* estimated with error. Thus, Monte Carlo simulation is again used to generate ten thousand vectors of simulated parameters based on the joint normal distributions of the parameters estimated in equations (10), (11), and (12). These vectors are generated as follows:

$$\hat{\boldsymbol{\lambda}}_j = \hat{\boldsymbol{\lambda}} + \mathbf{Q}'\mathbf{z}_j \text{, and } \mathbf{QQ}' = (\mathbf{X}'\boldsymbol{\Sigma}^{-1}\mathbf{X})^{-1} \tag{16}$$

where $\hat{\boldsymbol{\lambda}}_j$ is the j^{th} simulated 6 by 1 vector of parameter estimates based on the estimated system in equations (10), (11) and (12)—i.e., $\hat{\lambda}_{0j}$, $\hat{\lambda}_{1j}$, γ_{0j}, γ_{1j}, ρ_{0j}, and ρ_{1j}; $\hat{\boldsymbol{\lambda}}$ is the 6 by 1 vector of estimated parameters from equations (10), (11) and (12); $\mathbf{Q}'$ is the lower triangular Cholesky decomposition of $(\mathbf{X}'\boldsymbol{\Sigma}^{-1}\mathbf{X})^{-1}$, which is the 6 by 6 variance-covariance matrix of the parameters in $\hat{\boldsymbol{\lambda}}$, where:

$$\mathbf{X} = \begin{bmatrix} \mathbf{X_1} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{X_2} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{X_3} \end{bmatrix} \text{ and } \boldsymbol{\Sigma}^{-1} = \boldsymbol{\Sigma}_c^{-1} \otimes \mathbf{I}, \tag{17}$$

such that $\mathbf{X_1}$, $\mathbf{X}_2$ and $\mathbf{X}_3$ are the n by 2 matrices with n 1s and n N recommendations from equations (10), (11) and (12); and $\boldsymbol{\Sigma}_c$ and $\mathbf{I}$ are defined in equation (13).

Then, using the Monte Carlo simulated parameters from equation (16), the simulated parameters of the LRP functions of NDVI for each site-year—see equations (9) and (14)—are transformed from NDVI parameters to expected yield LRP parameters as follows:

(18) $$\tilde{\beta}_{0jt} = \hat{\lambda}_{0j} + \hat{\lambda}_{1j}\hat{\alpha}_{0jt},$$

(19) $$\tilde{\beta}_{1jt} = \hat{\gamma}_{0j} + \hat{\gamma}_{1j}\hat{\alpha}_{1jt}, \text{ and}$$

(20) $$\tilde{P}_{jt} = \hat{\rho}_{0j} + \hat{\rho}_{1j}\hat{\phi}_{jt}$$

where $\tilde{\beta}_{0jt}$, $\tilde{\beta}_{1jt}$ and $\tilde{P}_{jt}$ are, respectively, the j^{th} simulated intercept, slope and plateau coefficients of the predicted expected yield LRP function for site-year *t*; $\hat{\alpha}_{0jt}$, $\hat{\alpha}_{1jt}$ and $\hat{\phi}_{jt}$ are the j^{th} simulated intercept, slope and plateau coefficients, respectively, of the LRP function of NDVI measures for site-year *t*; $\hat{\lambda}_{0j}$, $\hat{\lambda}_{1j}$, $\hat{\gamma}_{0j}$, $\hat{\gamma}_{1j}$, $\hat{\rho}_{0j}$ and $\hat{\rho}_{1j}$ comprise the j^{th} simulated set of parameters relating LRP functions of yield and NDVI. $\tilde{\beta}_{0jt}$, $\tilde{\beta}_{1jt}$ and $\tilde{P}_{jt}$ in place of $\hat{\beta}_{0jt}$, $\hat{\beta}_{1jt}$ and $\hat{P}_{jt}$ in equation (15) to calculate the predicted expected profit maximizing N application rate.

Nitrogen Needs Predictions by Region-Year

The process for making region-year predictions of the economically optimal N application rate is similar to the process for obtaining site-year predictions. To begin, data from all sites in a given year are pooled to estimate:

(21) $$insey_{iy} = \min(\alpha_{0y} + \alpha_{1y}N_{iy}, \phi_y) + \varepsilon_{iy},$$

where $insey_{iy}$ is the NDVI measure on plot *i* in year *y*; α_{0y}, α_{1y}, ϕ_y are, respectively, the intercept, slope, and plateau of the LRP response of NDVI measures to N application in year *y*; N_{iy} is the N application rate on plot *i* in year *y*; and ε_{iy} is a stochastic error term with mean zero and variance σ_ε^2. The parameter estimates from equation (21) are then used with their estimated variance-covariance matrix to simulate ten thousand 4 by 1 vectors of parameters. These simulated parameters are transformed to parameters of expected yield LRP functions of N using the process described in equations (18), (19) and (20). Finally, these simulated parameters are used to predict the optimal topdress N application rate for the state-wide region in year *y* using the maximization problem in equation (15).

Calculation of Expected Yield and Expected Profit

Next, because one of the major objectives of this paper is to estimate the differences in relative profitability between the perfect predictor, the site-year-specific predictor, the region-year predictor and the historically recommended extension rate, the expected yield and expected profit are calculated for each system in each site-year as follows:

(22) $$E[y(N_{kt})] = \sum_{j=1}^{J} \frac{\min(\hat{\beta}_{0jt} + \hat{\beta}_{1jt} N_{kt}, \hat{P}_{jt})}{J},$$

(23) $$E[\pi(N_{kt})] = \sum_{j=1}^{J} \frac{p_c \min(\hat{\beta}_{0jt} + \hat{\beta}_{1jt} N_{kt}, \hat{P}_{jt})}{J} - p_n N_{kt} - p_a \delta_{kt} - p_k,$$

where *y* is yield; N_{kt} is the N application rate prescribed by system *k* for site-year *t*; $\hat{\beta}_{0jt}$ is the j^{th} simulated intercept coefficient of the yield response function for site-year *t*; $\hat{\beta}_{1jt}$

is the j^{th} simulated slope coefficient of the production function in site-year t; $\hat{P}_{jt}$ is the j^{th} simulated yield plateau for site-year t; δ_{kt} is an indicator variable equal to one if $N_{kt} > 0$ and zero otherwise; p_k is the cost of acquiring and using the information set for system k; k is either the region-year, site-year, historical extension rate, or perfect prediction system; and all other symbols are previously defined.

Testing for Differences in Expected Profit, Expected Yield, and Nitrogen Application Rates

Based on the calculations of expected yields and profits in equations (23) and (24), and the predicted economically optimal N application rates for each system and site-year, paired differences tests are used to determine whether any statistically significant differences exists between three systems in terms of yields, profitability and N use. These paired differences are calculated as:

(24) $$D_{qkt}^{y} = E[y(N_{qt})] - E[y(N_{kt})], \qquad q \neq k$$

(25) $$D_{qkt}^{\pi} = E[\pi(N_{qt})] - E[\pi(N_{kt})], \qquad q \neq k \text{, and}$$

(26) $$D_{qkt}^{N} = (N_{qt}) - (N_{kt}), \qquad q \neq k \text{,}$$

where D_{qkt}^{y} is the difference between the expected yield for methods q and k in site-year t; N_{qt} is the amount of N prescribed by system q in site-year t; N_{kt} is the N application rate prescribed by method k in site-year t; D_{qkt}^{π} is the difference of expected profit from methods q and k for site-year t; D_{qkt}^{N} is the difference of the N application rates prescribed by methods q and k for site-year t; methods q and k are two N application recommendation systems selected from the site-year, region-year, historical extension, and perfect predictor systems; and all other symbols are previously defined.

Because the student's *t* test relies on normality of the data, nonparametric bootstrapping of these differences is performed to test the null hypothesis that the mean paired differences of profits, yields and N application rates are zero. This is done by random sampling with replacement from the original sample of observations on the 52 site-years[2] to create ten thousand random samples of 52 site-years each. Using the means of the sample means and simulated standard errors (i.e., standard deviations of the sample means), *t* tests are conducted to determine whether the site-year, region-year, or historical extension recommendation system should be recommended for expected profit maximization.

Sensitivity analysis is performed to determine whether the results are sensitive to assumptions about NUE from topdress N application, as compared with preplant N application. NUE levels assumed for the purpose of sensitivity analysis are 32%, 45% and 50%—with 32% being the average NUE for preplant N applications (Roberts, 2009; Raun et al., 1999), 50% being the NUE for topdress applications assumed by Raun et al. (2005) and 45% being an intermediate level of NUE. These assumed levels of NUE correspond to multiplying Monte Carlo simulated slope parameters for topdress systems by 1, 1.41 and 1.56, respectively, before solving for the optimal N application rates and proceeding with the calculation of expected profits and yields.

[2] The original sample contains 53 site-years; however, experiments were only conducted at one location in 2007. As a result, a region-year N application could not be calculated for the Lahoma site in 2007.

Table I-8. Wheat Yield as a Function of Nitrogen Application with Site- and Year-Specific Effects on the Intercept and Plateau Yields

		Model		
Parameter	Definition	Unrestricted	No Plateau Random Effects	No Plateau Fixed Effects
β_0	Expected intercept yield	4144.99***[a] (196.52)[b]	3699.72*** (182.26)	4327.57*** (172.44)
β_1	Crop response to nitrogen	19.41*** (1.70)	19.30*** (1.79)	65.45*** (15.98)
P	Expected yield plateau	5522.14*** (188.54)	5535.95*** (175.22)	5243.81*** (154.43)
σ_u^2	Variance of error term	631321.00*** (26599.00)	677913.00*** (28651.00)	729510.00*** (30954.00)
σ_ε^2	Variance of intercept random effects for year	167307.00*** (23791.00)	188344.00*** (20907.00)	144457.00*** (31221.00)
σ_υ^2	Variance of plateau random effects for year	170663.00*** (33424.00)	-	208312.00*** (40004.00)
σ_ν^2	Variance of intercept fixed effects for site	51143301.00*** (9613634.00)	38989411.00*** (7422990.00)	61587700.00*** (8685127.00)
σ_ω^2	Variance of plateau fixed effects for site	13124989.00*** (1610810.00)	14357724.00*** (4374240.00)	-
Log Likelihood		-9187.50	-9203.50	-9251.50

[a] Three asterisks (*) indicate statistical significance at the 0.01 confidence level.
[b] Numbers in parentheses are standard errors.

Results

Table I-8 contains estimates of the parameters from equation (5), where wheat yield is a function of site, year and the preplant N application rate. The unrestricted model allows plateau and intercept yields to vary by site and year—i.e., $\sigma_\varepsilon^2, \sigma_\upsilon^2, \sigma_\nu^2, \sigma_\omega^2 > 0$. The model with no plateau random effects is restricted such that $\sigma_\upsilon^2 = 0$, limiting the model so that the average plateau yield across all locations does not vary by year. The likelihood ratio statistic—$LR = -2(-9203.50 + 9187.5) = 32.00$—is distributed chi-square with one degree of freedom, and exceeds the critical value at the 0.01 confidence level (6.64). This result indicates that the average plateau yield for the entire state of Oklahoma varies consistently by year. The implication is that if these annual effects on the plateau yield are predictable over a large region, NDVI data from locations (experiment stations, for example) dispersed throughout the region would provide valuable information to all producers therein. However, at the statewide level, the variability represented in the annual plateau effects is only about 10% of the total plateau variability—i.e., $\sigma_\upsilon / (\sigma_\upsilon + \sigma_\omega) = 0.10$. At the state level, annual effects have relatively little (albeit statistically significant) influence on N requirements; however, this may not be trivial. For example, if a perfect predictor—accounting for both field and annual effects—improves profit above the current practice by \$7.01 ha^{-1}(Roberts, 2009), a system that perfectly predicts annual effects would improve profits by about \$0.70 ha^{-1}. It is also possible that at smaller spatial resolutions, such as at the county level, annual effects might play a relatively larger role in variation of N requirements.

The model with no plateau fixed effects is restricted such that $\omega_i = 0, \forall\, i$ — meaning that there is no individual effect on the average plateau yield for site *i* within the state of Oklahoma. Given $\omega_i = 0$, the restriction may also be expressed as $\sigma_\omega^2 = 0$; however, because the model is estimated with fixed effects for site, the likelihood ratio statistic has nine degrees of freedom—i.e., the number of fixed effects estimated. The likelihood ratio statistic for this test is $LR = -2(-9251.50 + 9187.50) = 128.00$, which exceeds the chi-square critical value of 21.67, indicating that the average plateau yield over all years varies from site to site. Farmers who have field-specific experience and expectations could then adjust their expectations (and topdress N applications) annually based on midseason regional NDVI data collected at agricultural experiment stations and disseminated by the Cooperative Extension Service.

Tables I-9 and I-10 contain the estimated LRP parameters for yield and NDVI data as functions of preplant N for each site-year from equations (8) and (9), respectively. Table I-11 displays the results from the annual, state-wide estimation of the LRP function of NDVI as a function of N from equation (21). As noted in these tables, some of the estimated parameters have no standard errors. This occurs because the data for some site-years do not reach a plateau. In these cases, PROC NLMIXED estimated a linear model, but generated a plateau equal to the expected yield at the maximum rate applied in the data for these site-years. These estimates without standard errors are biased downward, because they tell us only that the plateau is expected to be greater than or equal to the estimate. This is also the case for estimates of the slope given without standard errors. At the Lahoma site in 2007, for instance, it appears "likely" that no data points are found on the slope of the production function. Figure I-12 illustrates this type of data limitation. In such instances, the estimate is a lower bound on the expected value of the slope parameter. The dashed lines show how the true production function might deviate from the estimated function, but exactly how the true slope deviates from the parameter estimated in PROC NLMIXED is uncertain. Additionally, for the Perkins 1 site in 2001 there are no standard errors for the intercept or plateau parameters. In this case, PROC NLMIXED estimated the mean yield for the site-year, but failed to provide standard errors because of data constraints. The fact that all points occur on the plateau means Monte Carlo simulation to account for estimation uncertainty is unnecessary because the

Table I-9. Estimated Wheat Yield Response to Nitrogen by Site-Year

Site	Year	Intercept	Slope	Plateau
Perkins 1	1998	1134.16***[a]	8.30***	2102.70***
		(132.79)[b]	(1.80)	(131.46)
Perkins 2	1998	1316.98***	1.22	1487.41***
		(94.25)	(1.30)	(107.84)
Tipton	1998	2942.65***	12.46***	5037.68***
		(93.34)	(0.43)	(21.57)
Efaw 1	1999	1040.52***	5.46***	3068.36***
		(226.84)	(1.50)	(323.60)
Efaw 2	1999	2169.07***	19.27***	3514.67***
		(192.95)	(4.22)	(96.48)
Haskell	1999	1767.41***	7.71[c]	2072.13***
		(288.21)		(182.28)
Lahoma	1999	1515.22***	26.28***	4443.08***
		(116.66)	(2.28)	(181.36)
Perkins 1	1999	1077.20***	12.71**	2431.26***
		(177.94)	(4.49)	(125.83)
Stillwater	1999	856.12***	10.90**	1712.27***
		(103.51)	(4.00)	(110.65)
Efaw 1	2000	911.11**	26.84***	3384.06***
		(380.28)	(6.57)	(294.56)
Efaw 2	2000	2246.40***	-1.53	2160.87***
		(579.52)	(6.18)	(415.54)
Haskell	2000	4262.17***	-13.77***	2719.13***
		(212.53)	(1.20)	(212.53)
Hennessey	2000	3833.55***	-0.29	3817.26***
		(453.84)	(4.84)	(324.55)
Lahoma	2000	1944.08***	25.03***	3515.75***
		(152.73)	(6.09)	(130.79)
Perkins 1	2000	2599.85***	6.55	3333.56***
		(714.43)	(14.72)	(319.59)
Stillwater	2000	1120.71***	17.05***	3414.03***
		(83.13)	(1.34)	(96.79)
Efaw 1	2001	921.82***	15.52**	2024.16***
		(215.47)	(6.80)	(112.53)
Efaw 2	2001	2693.37***	8.80	3301.97***
		(285.19)	(6.23)	(142.60)
Haskell	2001	3669.98**	-6.77	3121.59***
		(1368.34)	(10.92)	(387.02)

Table I-9. Estimated Wheat Yield Response to Nitrogen by Site-Year

Site	Year	Intercept	Slope	Plateau
Hennessey	2001	1951.38***	7.01***	2815.16***
		(184.75)	(0.76)	(91.34)
Lahoma	2001	1495.54***	3.48	1651.35***
		(201.16)	(17.18)	(142.25)
Perkins 1	2001	2602.15[d]	-1.35	2602.15[d]
			(1.09)	
Stillwater	2001	1054.21***	12.70**	1636.39***
		(142.89)	(5.52)	(142.89)
Efaw 1	2002	732.37**	30.95***	2705.91***
		(325.25)	(10.26)	(178.15)
Efaw 2	2002	1811.65***	19.95***	3575.11***
		(305.03)	(6.67)	(152.52)
Haskell	2002	3500.96***	-13.98*	3112.43***
		(938.17)	(1.45)	(262.23)
Hennessey	2002	3898.07***	-10.17***	2986.17***
		(28.52)	(2.44)	(189.00)
Lahoma	2002	2711.28***	16.54[c]	3075.88***
		(194.42)		(122.96)
Perkins 1	2002	2711.83***	1.55***	2971.97***
		(192.26)	(0.18)	(161.91)
Stillwater	2002	961.60***	16.03***	2987.25***
		(77.43)	(1.54)	(114.85)
Efaw 1	2003	1077.11**	24.02***	3996.63***
		(477.42)	(8.25)	(320.26)
Efaw 2	2003	2792.10***	20.31***	4950.90***
		(403.20)	(6.03)	(312.61)
Hennessey	2003	2337.13***	14.67***	3760.42***
		(256.09)	(3.65)	(166.31)
Lahoma	2003	2760.86***	46.43***	5716.37***
		(209.35)	(8.30)	(177.55)
Perkins 1	2003	2796.69***	12.81**	3779.32***
		(190.99)	(4.82)	(135.05)
Stillwater	2003	1136.43***	19.88***	2473.30***
		(176.83)	(6.86)	(144.36)
Efaw 1	2004	2079.37***	22.90	4132.65***
		(570.45)	(18.01)	(285.13)
Lahoma	2004	1871.40***	29.23[c]	2526.56***
		(313.47)		(198.26)

Table I-9. Estimated Wheat Yield Response to Nitrogen by Site-Year

Site	Year	Intercept	Slope	Plateau
Lake C.B.	2004	2227.34^{***}	18.21^{***}	4063.86^{***}
		(248.19)	(2.14)	(32.38)
Perkins 1	2004	1936.34^{***}	19.77^{*}	3399.90^{***}
		(393.48)	(9.93)	(278.24)
Stillwater	2004	2080.99	-2.77	1895.02^{***}
		(2250.37)	(28.29)	(220.59)
Efaw 1	2005	1164.41^{***}	4.56^{***}	2845.72^{***}
		(210.37)	(1.39)	(300.10)
Lahoma	2005	1754.09^{***}	18.44^{**}	2683.34^{***}
		(188.07)	(7.27)	(151.63)
Perkins 1	2005	3494.44^{***}	9.84[c]	4021.48^{***}
		(267.04)		(178.03)
Stillwater	2005	1764.35^{***}	15.36	2223.53^{***}
		(145.62)		(118.90)
Efaw 1	2006	1081.14^{***}	8.05	2291.79^{***}
		(275.92)	(4.77)	(174.51)
Lahoma	2006	2229.78^{***}	4.03	2680.96[c]
		(199.48)	(3.18)	
Lake C.B.	2006	1277.42^{***}	37.69^{***}	4377.41^{***}
		(291.04)	(8.16)	(291.04)
Perkins 1	2006	917.24^{***}	12.33^{***}	2053.63^{***}
		(113.69)	(2.87)	(80.39)
Stillwater	2006	1333.57^{***}	-5.64^{***}	772.77^{***}
		(0.17)	(0.68)	(40.72)
Lahoma	2007	2540.65^{***}	28.81[c]	3162.98^{***}
		(177.01)		(129.27)
Lahoma	2008	2761.46^{***}	59.55^{***}	5525.64^{***}
		(294.09)	(11.73)	(251.85)
Stillwater	2008	1381.12	15.99^{***}	2697.59^{***}
		(174.25)	(4.31)	(251.12)
Mean for all site-years		2004.70^{***}	13.19^{***}	3071.95^{***}
		(124.73)	(1.92)	(139.93)

Note: Units are kg ha^{-1}.
[a] One, two, or three asterisks (*) indicate statistical significance at the 0.10, 0.05 or 0.01 level, respectively.
[b] Numbers in parentheses are standard errors.
[c] Standard error cannot be estimated due to lack of data points on the slope or plateau. The estimated parameter is biased downward.
[d] Standard errors for the intercept and plateau are not estimated because all available data are on the plateau.

Table I-10. Estimated Wheat Optical Reflectance Response to Nitrogen by Site-Year, Scaled by a Factor of Ten Thousand

Site	Year	Intercept	Slope	Plateau
Perkins 1	1998	595.56***[a] (24.82)[b]	1.60*** (0.34)	804.24*** (25.90)
Perkins 2	1998	571.95*** (23.12)	0.87 (0.58)	663.34*** (16.35)
Tipton	1998	693.77*** (8.83)	1.18*** (2.23)	804.08*** (6.20)
Efaw 1	1999	383.81*** (32.08)	3.34*** (1.01)	618.43*** (16.04)
Efaw 2	1999	693.32*** (17.56)	1.44*** (0.38)	783.52*** (8.71)
Haskell	1999	619.21*** (23.99)	2.29[c]	669.79*** (15.17)
Lahoma	1999	615.96*** (13.21)	2.04*** (0.35)	785.83*** (14.55)
Perkins 1	1999	466.16*** (23.44)	1.93*** (0.59)	591.37*** (16.48)
Stillwater	1999	553.76*** (32.94)	3.52[c]	634.99*** (26.90)
Efaw 1	2000	702.43*** (93.12)	7.82*** (1.61)	1488.30*** (72.13)
Efaw 2	2000	864.23*** (38.39)	7.21[c]	891.76*** (15.67)
Haskell	2000	600.48*** (37.85)	2.10[c]	625.01*** (23.94)
Hennessey	2000	961.20*** (2.36)	0.14 (0.22)	978.53*** (25.06)
Lahoma	2000	784.50*** (18.58)	5.10*** (0.74)	1092.05*** (15.92)
Perkins 1	2000	652.11*** (53.91)	3.99[c]	770.82*** (31.12)
Stillwater	2000	558.14*** (21.62)	7.19*** (0.84)	935.22*** (21.62)
Efaw 1	2001	627.63*** (37.81)	2.46*** (0.65)	876.16*** (25.37)
Efaw 2	2001	896.45*** (24.13)	0.21 (0.36)	922.09*** (18.71)
Haskell	2001	674.80*** (32.57)	0.36 (0.31)	822.37

Table I-10. Estimated Wheat Optical Reflectance Response to Nitrogen by Site-Year, Scaled by a Factor of Ten Thousand

Site	Year	Intercept	Slope	Plateau
Hennessey	2001	726.26***	1.29***	912.51[c]
		(48.56)	(0.56)	
Lahoma	2001	774.70***	0.82	805.71***
		(35.75)	(2.78)	(25.28)
Perkins 1	2001	834.69[d]	0[c]	834.69[d]
Stillwater	2001	677.06***	2.76	824.16***
		(42.71)	(1.65)	(42.71)
Efaw 1	2002	537.19***	2.39	649.67***
		(87.72)	(2.77)	(43.86)
Efaw 2	2002	638.31***	1.79***	742.28***
		(14.87)	(0.33)	(7.43)
Haskell	2002	517.16***	0.92	672.40***
		(7.65)	(1.25)	(202.60)
Hennessey	2002	652.30***	-0.39	616.92***
		(0.01)	(0.41)	(29.23)
Lahoma	2002	753.81***	4.24[c]	843.41***
		(48.93)		(30.94)
Perkins 1	2002	721.90***	0.35**	834.69[c]
		(13.34)	(0.13)	
Stillwater	2002	448.76***	3.71***	692.68***
		(13.06)	(0.50)	(13.03)
Efaw 1	2003	346.68***	1.55***	670.93***
		(37.06)	(0.36)	(33.83)
Efaw 2	2003	652.54***	1.38***	816.61***
		(36.81)	(0.55)	(28.54)
Hennessey	2003	876.40***	1.69	1073.04***
		(70.44)	(1.05)	(54.63)
Lahoma	2003	570.00***	9.00***	860.00***
		(1.39)	(1.39)	(11.94)
Perkins 1	2003	496.14***	1.20***	684.12[c]
		(19.24)	(0.18)	
Stillwater	2003	391.54***	3.71***	648.51***
		(25.24)	(0.62)	(25.72)
Efaw 1	2004	478.65***	3.40	781.76***
		(81.33)	(2.57)	(40.64)
Lahoma	2004	598.04	10.32[c]	757.59***
		(85.90)		(54.33)

Table I-10. Estimated Wheat Optical Reflectance Response to Nitrogen by Site-Year, Scaled by a Factor of Ten Thousand

Site	Year	Intercept	Slope	Plateau
Lake C.B.	2004	418.32***	2.20	639.75
		(46.44)	(9.16)	(877.19)
Perkins 1	2004	480.82***	1.17***	617.06***
		(14.34)	(0.20)	(15.70)
Stillwater	2004	727.06*	-2.45	564.32***
		(407.27)	(5.12)	(44.51)
Efaw 1	2005	497.75***	2.29***	763.08***
		(33.02)	(0.57)	(20.87)
Lahoma	2005	543.05***	3.20***	735.75***
		(15.09)	(0.59)	(12.11)
Perkins 1	2005	471.63***	1.33***	669.34***
		(21.72)	(0.32)	(26.93)
Stillwater	2005	550.07***	1.66***	699.18***
		(2.92)	(0.46)	(38.05)
Efaw 1	2006	306.18***	2.05**	527.35***
		(50.30)	(0.87)	(31.81)
Lahoma	2006	484.41***	4.78[c]	564.29***
		(30.91)		(19.55)
Lake C.B.	2006	501.91***	1.03	606.19***
		(4.79)	(0.80)	(76.37)
Perkins 1	2006	268.27***	2.20***	476.83***
		(24.38)	(0.62)	(17.25)
Stillwater	2006	354.27***	1.00***	488.87***
		(1.31)	(0.29)	(37.81)
Lahoma	2007	513.11***	3.22***	597.96***
		(12.08)	(0.93)	(8.54)
Lahoma	2008	508.56***	5.36***	912.38***
		(19.71)	(0.53)	(21.66)
Stillwater	2008	690.54***	1.82[c]	771.92***
		(68.31)		(55.78)
Mean for all site-years		594.78***	2.56***	756.87***
		(21.08)	(0.33)	(23.49)

[a] One, two, or three asterisks (*) indicate statistical significance at the 0.10, 0.05 or 0.01 level, respectively.
[b] Numbers in parentheses are standard errors.
[c] Standard error cannot be estimated due to lack of data points on the slope or plateau. The estimated parameter is biased downward.
[d] Standard errors for the intercept and plateau are not estimated because all available data are on the plateau.

Table I-11. Estimated Wheat Optical Reflectance Response to Nitrogen by Year, scaled by a Factor of Ten Thousand

Year[a]	Intercept	Slope	Plateau
1998	618.49***[b]	1.33***	749.34***
	(16.09)[c]	(0.40)	(11.19)
1999	576.33***	2.11***	685.08***
	(16.65)	(0.74)	(10.91)
2000	745.87***	1.64***	1187.04***
	(1.95)	(0.23)	(60.97)
2001	731.74***	1.81**	821.66***
	(19.02)	(0.88)	(11.80)
2002	646.57***	0.45	767.48***
	(18.50)	(1.96)	(80.44)
2003	537.63***	3.49***	792.95***
	(33.07)	(0.82)	(23.71)
2004	574.33***	1.21	677.89***
	(30.83)	(0.82)	(28.07)
2005	549.72***	1.57***	739.71***
	(12.66)	(0.21)	(19.17)
2006	427.00***	0.81**	534.13***
	(21.20)	(0.34)	(30.34)
2008	597.96***	3.40***	856.63***
	(30.92)	(0.80)	(37.95)

Note: Units are kg ha^{-1}.
[a] A response function for 2007 is not estimated because only one site is available in this year.
[b] Two or three asterisks (*) indicate statistical significance at the 0.05 or 0.01 level, respectively.
[c] Numbers in parentheses are standard errors.

mean is linear in parameters. Thus, the lack of standard errors for the plateau and intercept in this site-year is not problematic.

The estimated relationships between the parameters of NDVI and yield response—estimated in equations (10), (11) and (12)—are presented in table I-12. Here, the relationship describes how yield LRP function parameters (table I-9) depend upon midseason NDVI parameters (table I-10). The signs of the estimated coefficients are as expected—i.e., higher NDVI intercepts predict higher yield intercepts; higher NDVI response (slope) predicts higher yield response; and higher NDVI plateaus predict high

NDVI plateaus. Note based on the coefficients of variation for these relationships (R^2 in table I-12) that these relationships are very noisy. These parameters (and their variance-covariance matrix) are used to convert LRP parameters of NDVI response into expected yield response through Monte Carlo simulation described in equations (18) to (20). Nonparametrically bootstrapped means of the prescribed N application rates, expected yields, and return above N-related costs for each system are displayed in table I-13, assuming NUE of 32% for both preplant and topdress applications. Notably, mean net revenue is greatest for the historically recommended rate of 90 kg N ha^{-1} from NH_3, at \$639.92 ha^{-1}, but this is only slightly greater than the \$638.46 ha^{-1} earned by the perfect predictor. While N purchase costs are much lower for the historical rate—because it uses NH_3 rather than UAN—N *application* costs are much higher for the historical rate. The increased application cost, along with a slight yield boost for the perfect predictor system, nearly cancels out any saving on N purchase for the historical rate system.

Additionally, the mean recommended application rates for the field- and region-based N requirements predictors are 88.92 and 94.11 kg ha^{-1}, respectively—apparently not much different from the historically recommended rate. The field-based system does appear to have some predictive power (though not statistically significant) because it achieves slightly higher yield than the historical rate while applying slightly less N. However, the total costs of N purchase and application for the two NDVI-based systems are, respectively, \$107.52 and \$113.23 ha^{-1}—relatively high compared to the analogous costs of \$71.79 ha^{-1} for the historical rate system. This difference is primarily due to the relative prices of topdress UAN (\$1.10 kg^{-1}) and preplant NH_3 (\$0.57 kg^{-1}). It is possible that the field- and region- based systems could save substantially on N-related costs by

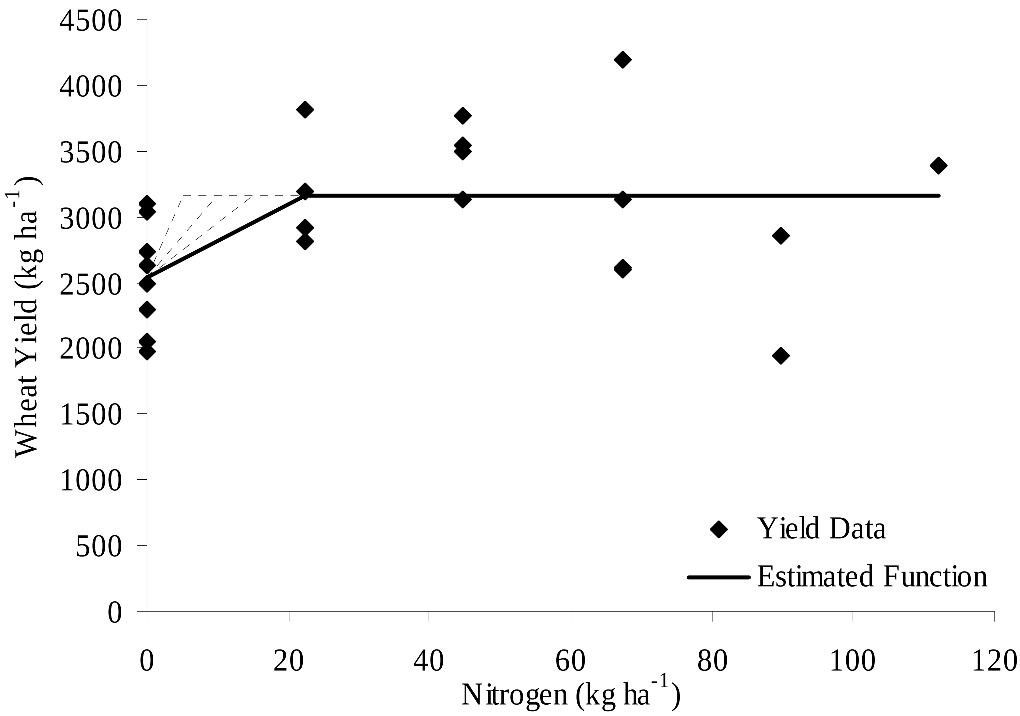

Figure I-12. Plot of yield data and estimated production function for Lahoma 2007.

using a split application—i.e., some N applied preplant as NH_3 and some as topdress UAN if the RS shows that the crop is responsive. The mean UAN rate applied by the perfect predictor system is 65.41 kg ha^{-1}, compared with about 90 kg ha^{-1} for either of the NDVI-based systems, meaning that the NDVI-based systems used in this paper over-apply N substantially, as expected.

Table I-14 shows the nonparametrically bootstrapped means of the paired differences of expected profits, expected N application and expected yield generated in equations (24), (25) and (26). These results confirm that the profitability difference between the perfect predictor and the historical rate is statistically insignificant, despite the historical N application rate being on average 24.60 kg ha^{-1} higher than the perfect predictor rate. Recall from table I-3 that the "perfect predictor" fails to provide the

Table I-12. Response of Yield Intercepts, Slopes and Plateaus to Optical Reflectance Intercepts, Slopes and Plateau, Respectively, Estimated by Seemingly Unrelated Regression

Parameter	Definition	Estimate
λ_0	Intercept of intercept response	480.85
		(369.50)[a]
λ_1	Slope of intercept response	255830.70***[b]
		(59091.90)
R^2	Coefficient of determination	0.15
γ_0	Intercept of slope response	7.65***
		(2.06)
γ_1	Slope of slope response	217088.40***
		(48025.00)
R^2	Coefficient of determination	0.24
ρ_0	Intercept of plateau response	1440.23***
		(429.20)
ρ_1	Slope of plateau response	215697.40***
		(53847.50)
R^2	Coefficient of determination	0.09

[a] Numbers in parentheses are standard errors.
[b] Three asterisks (*) represent statistical significance at the 0.01 level.

maximum profit primarily because it is a topdress system, using expensive UAN in place of cheaper NH_3. Additionally, the perfect predictor system is significantly ($p < 0.01$) more profitable than either the field-based or the region-based predictors by \$35.14 ha^{-1} on average. The historically recommended application of 90 kg N ha^{-1} preplant is significantly more profitable than both the field- and region-based predictors by respective averages of \$36.60 and \$38.41 ha^{-1}. Expected profits from the field- and region-based systems are not statistically different.

Table I-15 displays the nonparametrically bootstrapped means of the prescribed N application rates, expected yields, and return above N-related costs for each system, assuming that NUE is 32% for preplant N applications and 45% for midseason topdress applications. Note that under this assumption, the perfect predictor system maximizes expected profit compared to the other systems (in contrast to the results in table I-13).

Table I-13. Noparametrically Bootstrapped Means of Net Returns, Revenues, Nitrogen-Related Costs, Yields and Nitrogen Application Rates for Each Application System, Assuming 32% Nitrogen-Use Efficiency for Both Topdress and Preplant Nitrogen Applications

	System			
Revenue/Cost	Perfect Predictor	Historical Rate	Field-Based Predictor	Region-Based Predictor
Net Revenue	638.46	639.92	603.32	601.51
($ ha^{-1})	(33.82)	(33.40)	(33.56)	(33.17)
Yield Revenue	717.51	711.71	713.88	714.73
($ ha^{-1})	(35.19)	(33.40)	(33.74)	(33.41)
NH_3 Cost	-	-51.30	-	-
($ ha^{-1})				
Mean UAN Cost	-71.85	-	-97.81	-103.52
($ ha^{-1})	(6.96)		(2.73)	(2.08)
NH_3 Application Cost	-	-20.49	-	-
($ ha^{-1})				
Mean UAN Application Cost	-7.10	-	-9.71	-9.71
($ ha^{-1})	(0.60)		(0.00)	(0.00)
Precision System Cost	-	-	-3.04	-
($ ha^{-1})				
Average Yield	2989.64	2965.46	2974.51	2978.05
(kg ha^{-1})	(146.61)	(139.19)	(140.60)	(139.23)
Mean UAN Rate	65.41	-	88.92	94.11
(kg ha^{-1})	(6.33)		(2.49)	(1.89)

Note: All estimates are significant at the 0.01 confidence level.

This is because assuming topdress NUE of 45% substantially increases the marginal product of topdress N, while leaving the marginal product of preplant N unchanged. Under this assumption, the bootstrapped mean N application for each topdress system is substantially reduced relative to those in table I-13. This occurs because an increase in the marginal product of N means that not as much N is required to reach the plateau. Also noteworthy is the result that expected yield for the topdress systems has increased, indicating that this increase in the marginal product of N makes UAN application more

Table I-14. Nonparametrically Bootstrapped Means of Paired Differences of Expected Profits, Expected Nitrogen Application Rates, and Expected Yields, Assuming 32% Nitrogen-Use Efficiencies for Both Preplant and Topdress Nitrogen Applications

Difference			Expected Profit ($\$$ ha^{-1})	Expected Nitrogen Rate (kg ha^{-1})	Expected Yield (kg ha^{-1})
Perfect Predictor	-	Historical Rate	-1.46 (5.31)[a]	-24.60*** (6.33)	24.18 (26.33)
Perfect Predictor	-	Field-Based Predictor	35.14***[b] (5.51)	-23.51*** (5.91)	15.13 (26.78)
Perfect Predictor	-	Region-Based Predictor	36.95*** (5.69)	-28.70*** (6.74)	11.58 (27.36)
Historical Rate	-	Field-Based Predictor	36.60*** (2.61)	1.08 (2.49)	-9.05 (13.15)
Historical Rate	-	Region-Based Predictor	38.41*** (2.45)	-4.11** (1.89)	-12.60 (12.03)
Field-Based Predictor	-	Region-Based Predictor	1.81 (4.10)	-5.18 (3.28)	-3.55 (19.72)

[a] Numbers in parentheses are standard errors.
[b] Two or three asterisks (*) indicate statistical significance at the 0.05 or 0.01 level, respectively.

profitable than it otherwise would be, specifically in site-years where the slope of the response to *preplant* N is small.

Table I-16 contains the bootstrapped means of the paired differences of expected profit, expected N application rate and expected yield for each system, assuming 32% and 45% NUE for preplant and topdress applications. These results confirm that the profitability difference of $24.98—favoring the perfect predictor system over the historical recommendation—is statistically significant at the 0.01 confidence level. The perfect predictor system continues to be more profitable than the field- and region-based systems. Notably, though the mean profit paired differences between the historical rate system and the field- and region-based systems continue to be significant in favor of the historical rate—$6.91 and $9.73 ha^{-1}, respectively—the differences are smaller in magnitude compared to those in table I-15. There still is no statistically significant

Table I-15. Noparametrically Bootstrapped Means of Net Returns, Revenues, Nitrogen-Related Costs, Yields and Nitrogen Application Rates for Each Application System, Assuming 32% and 45% Nitrogen-Use Efficiency for Preplant and Topdress Nitrogen Applications, Respectively

	System			
Revenue/Cost	Perfect Predictor	Historical Rate	Field-Based Predictor	Region-Based Predictor
Net Revenue	664.90	639.12	633.01	630.19
($ ha^{-1})	(34.32)	(33.40)	(33.48)	(33.14)
Yield Revenue	728.52	711.71	718.80	721.25
($ ha^{-1})	(35.51)	(33.40)	(33.60)	(33.48)
NH_3 Cost	-	-51.30	-	-
($ ha^{-1})				
Mean UAN Cost	-56.33	-	-73.05	-81.35
($ ha^{-1})	(5.57)		(2.29)	(2.48)
NH_3 Application Cost	-	-20.49	-	-
($ ha^{-1})				
Mean UAN Application Cost	-7.29	-	-9.71	-9.71
($ ha^{-1})	(0.58)		(0.00)	(0.00)
Precision System Cost	-	-	-3.04	-
($ ha^{-1})			(0.00)	
Average Yield	3035.49	2965.46	2995.01	3005.19
(kg ha^{-1})	(147.96)	(139.19)	(140.00)	(139.52)
Mean UAN Rate	51.21	-	66.41	73.95
(kg ha^{-1})	(5.06)		(2.09)	(2.25)

Note: All estimates are significant at the 0.01 confidence level.

difference between the field- and region-based systems in terms of profitability, though the region-based system applies more N by an average of 7.55 kg ha^{-1} ($p < 0.05$).

The nonparametrically bootstrapped means of prescribed N application rates, expected yields, and return above N-related costs for each system assuming 32% and 50% NUE for preplant and topdress N, respectively, are presented in table I-17. Here, the field- and region-based predictors have returns (net of N-related costs) very similar to the returns from using the historical rate. The mean of expected net revenue is slightly higher for the field-based system and slightly lower for the region-based system. The costs of N

Table I-16. Nonparametrically Bootstrapped Means of Paired Differences of Expected Profits, Expected Nitrogen Application Rates, and Expected Yields, Assuming 32% and 45% Nitrogen-Use Efficiencies for Preplant and Topdress Nitrogen Applications, Respectively

Difference			Expected Profit ($\$$ ha^{-1})	Expected Nitrogen Rate (kg ha^{-1})	Expected Yield (kg ha^{-1})
Perfect Predictor	-	Historical Rate	24.98***[a] (5.43)[b]	-38.79*** (5.06)	70.03** (34.25)
Perfect Predictor	-	Field-Based Predictor	31.90*** (5.72)	-15.20*** (4.84)	40.48 (32.38)
Perfect Predictor	-	Region-Based Predictor	34.71*** (5.55)	-22.75*** (5.80)	30.30 (30.82)
Historical Rate	-	Field-Based Predictor	6.91** (2.96)	23.59*** (2.09)	-29.55* (16.56)
Historical Rate	-	Region-Based Predictor	9.73*** (3.42)	16.05*** (2.25)	-39.73** (15.89)
Field-Based Predictor	-	Region-Based Predictor	2.82 (4.89)	-7.55** (3.39)	-10.18 (24.37)

[a] One, two or three asterisks indicate statistical significance at the 0.10, 0.05 or 0.01 confidence level, respectively.
[b] Numbers in parentheses are standard errors.

purchase and application for the historical, field-based and region based systems are$71.79, $76.89 and $84.54 ha^{-1}, respectively. The field- and region-based systems make up for their increased N expenditures (and the cost of the RS, in the case of the field-based system) through increased yields resulting from higher NUE.

Table I-18 presents the nonparametrically bootstrapped means of the paired differences of expected profits, expected N application rates and expected yields between the four systems. Note that the perfect predictor system is expected to be more profitable than all other systems by at least $31.74 ha^{-1}, and that these differences are statistically significant at the 0.01 confidence level. Additionally, the historical rate is higher than the mean of any other system by at least 21.79 kg N ha^{-1}. One problem with the field- and

Table I-17. Noparametrically Bootstrapped Means of Net Returns, Revenues, Nitrogen-Related Costs, Yields and Nitrogen Application Rates for Each Application System, Assuming 32% and 50% Nitrogen-Use Efficiency for Preplant and Topdress Nitrogen Applications, Respectively

	System			
Revenue/Cost	Perfect Predictor	Historical Rate	Field-Based Predictor	Region-Based Predictor
Net Revenue	671.84	639.12	640.10	638.01
($ ha^{-1})	(34.09)	(33.40)	(33.54)	(33.18)
Yield Revenue	734.11	711.71	720.03	722.55
($ ha^{-1})	(34.64)	(33.40)	(33.66)	(33.50)
NH_3 Cost	-	-51.30	-	-
($ ha^{-1})				
Mean UAN Cost	-54.79	-	-67.18	-74.83
($ ha^{-1})	(5.28)		(2.12)	(2.29)
NH_3 Application Cost	-	-20.49	-	-
($ ha^{-1})				
Mean UAN Application Cost	-7.48	-	-9.71	-9.71
($ ha^{-1})	(0.56)		(0.00)	(0.00)
Precision System Cost	-	-	-3.04	-
($ ha^{-1})			(0.00)	
Average Yield	3058.81	2965.46	3000.14	3010.62
(kg ha^{-1})	(144.33)	(139.19)	(140.27)	(139.57)
Mean UAN Rate	49.81	-	61.07	68.03
(kg ha^{-1})	(4.80)		(1.93)	(2.08)

Note: All estimates are significant at the 0.01 confidence level.

region-based systems as developed in this paper is that they always recommend some level of N application. This is evident because mean application costs for these systems, regardless of assumptions about NUE are $9.71 ha^{-1} (see tables I-13, I-15 and I-17). As a result, field- and region-based methods used here apply substantial N in cases where the true expected profit maximizing N rate is actually zero. This results in a substantial increase in N costs relative to the perfect predictor system without a commensurate increase in yield (because yield reaches a plateau at many sites at 65 kg N ha^{-1}).

Table I-18. Nonparametrically Bootstrapped Means of Paired Differences of Expected Profits, Expected Nitrogen Application Rates, and Expected Yields, Assuming 32% and 50% Nitrogen-Use Efficiencies for Preplant and Topdress Nitrogen Applications, Respectively

Difference			Expected Profit ($ ha^{-1})	Expected Nitrogen Rate (kg ha^{-1})	Expected Yield (kg ha^{-1})
Perfect Predictor	-	Historical Rate	31.92***	-40.18***	93.35***
			(5.39)	(4.80)	(34.14)
Perfect Predictor	-	Field-Based Predictor	31.74***	-11.26**	58.67*
			(5.57)	(4.52)	(31.07)
Perfect Predictor	-	Region-Based Predictor	33.83***	-18.21***	48.19
			(5.21)	(5.46)	(29.41)
Historical Rate	-	Field-Based Predictor	-0.18	28.93***	-34.68**
			(3.03)	(1.93)	(16.75)
Historical Rate	-	Region-Based Predictor	1.91	21.97***	-45.16***
			(3.48)	(2.08)	(16.12)
Field-Based Predictor	-	Region-Based Predictor	2.09	-6.96**	-10.48
			(4.85)	(3.13)	(24.24)

[a] One, two or three asterisks indicate statistical significance at the 0.10, 0.05 or 0.01 confidence level, respectively.
[b] Numbers in parentheses are standard errors.

Also noteworthy is that the value of a perfect predictor system—i.e., the profit difference between the perfect predictor and the second most profitable system—is highly dependent on NUE. If NUE for topdress applications is the same as for preplant applications (32%), a perfect prediction of topdress N requirements has no value (see table I-15). On the other hand tables I-17 and I-19 indicate that the value of a perfect predictor given 45% and 50% NUE is $24.98 or $31.74 ha^{-1}, respectively. Thus, the value of a perfect predictor of topdress N requirements is strongly dependent on the true NUE for topdress applications.

Conclusions

One important finding of this research is that the historical extension recommendation—i.e., 90 kg N ha^{-1} as NH_3—is statistically indistinguishable from the "perfect predictor" topdress application system using UAN, primarily resulting from relative costs of UAN (\$1.10 kg^{-1}) and NH_3 (\$0.56 kg^{-1}). The value of a perfect predictor, or the mean difference between the perfect predictor and the second-best method, is found to be highly dependent on assumptions about NUE. The value of a perfect predictor is \$31.92 ha^{-1} if NUE is 50% for topdress and 32% for preplant N. However, if NUE is 32% for both topdress and preplant N, the perfect predictor has no value relative to the historical extension advice. Because the assumption about NUE seems to be so critical, continued research should be dedicated to determining how topdress and preplant NUE correlate with each other and with NDVI data.

The site-year- and region-year-specific predictors based on midseason NDVI measures are poor predictors of actual N requirements. Expected profits from these two systems are also statistically indistinguishable, regardless of assumptions about NUE. This is likely due to the large amount of statistical noise in the relationship between NDVI and yield. The methods used in this paper are based on the RS method of N requirements prediction, but do not follow the same procedures in making prediction. For example, the data used here are not collected from actual RSs, but from plots at experiment stations. Additionally, the RS contains more N treatment levels than the data used here. The experimental data used in this paper, however, include several replications of each treatment level at different plots. Additionally, the data used to make the predictions come from the same plots as the data used to estimate the yield functions and calculate profits. That is, all models are estimated in-sample, which should be an advantage to the NDVI-based predictors. Surprisingly, however, these advantages do not translate into improved profits for the site-year and region-year N requirements predictors relative to the historical extension advice, regardless of assumptions about NUE.

While evidence supports the hypothesis that N requirements vary by year and location (table I-8 and associated hypothesis tests), this variability must be detectable and predictable for use in N application decisions. Thus, the question of whether NDVI-based predictions of N needs vary together by time and location is of great importance. However, the NDVI-based systems in this paper do not detect such variability. Despite accounting for only a small portion of the variability of crop N requirements, however, an accurate regional prediction system might still increase profits for producers because the N requirements information would be provided free of charge.

Also, it should be noted that the cost of the sensor and establishing a RS is small relative to the other variables that determine profitability of the field- and region-based systems. The cost of using the RS technology in each field is different, though, for producers who grow wheat for both grazing and grain, and these might prefer a region-based prediction system. Based on the results in table I-13, the optimal strategy may be to use a split application in which some N is applied preplant as NH_3 and then NDVI data are used midseason to determine whether the crop will respond to additional N. Doing so could save substantial N purchase costs for a producer by replacing some UAN with NH_3, and potentially eliminating the need for UAN in some years. The optimal level of preplant N in a split application system that uses NDVI data to predict topdress N rates could be determined by a grid search based on the production functions and predictions in this paper. However, the results of such a grid search would be fragile to assumptions about NUE.

An experiment that does not depend on assumptions about NUE should be conducted. An example of such an experiment is one that applies varying levels of preplant NH_3 to randomized, replicated plots in fields at several different sites throughout the state, and then superimposes varied rates of midseason topdress UAN on those same plots at random, including some topdress rates based on optical sensing methods. The experiment would be conducted for several years, and would collect both optical reflectance and yield data from the plots. The experimental data could then be used to determine the relative profitability of strategies that apply different rates of preplant NH_3 prior to sensing and topdress UAN application, as well as the relative profitability of strategies that predict N requirements based on NDVI data sampled at different spatial resolutions to make N requirement predictions.

Finally, previous studies have shown that deterministic N needs prediction systems predict N requirements much lower than 90 kg ha^{-1}. Biermacher et al. (2008) found that the NFOA recommended an average of 24.5 kg N ha^{-1} for 19 different site-years, whereas the NDVI-based methods used in this paper (based on the ramped strip technology) recommend an average application rate of about 90 kg ha^{-1}. Roberts (2009) found that addressing parameter uncertainty alone (not including prediction error) increases the predicted N requirements from the NFOA from 30.38 to 42.13 kg N ha^{-1}. Thus, the noise in the predictive models and the error of estimation mean that the optimal level of N application is higher than what has been predicted previously by deterministic algorithms. This means that under uncertainty, savings on N purchases will be eroded to reduce the risk of relatively costly yield losses.

CHAPTER II

THE EFFECT OF PARAMETER UNCERTAINTY ON NITROGEN RECOMMENDATIONS FROM NITROGEN-RICH STRIPS AND RAMPED STRIPS IN WINTER WHEAT

Abstract

This paper estimates the relative profitability of four different optical reflectance-based predictors of crop needs for topdress nitrogen application to winter wheat. The data come from randomized experimental plots on which nitrogen application levels varied, from which midseason optical reflectance data and wheat yield measures were collected. These data are used to approximate data from nitrogen-rich strips (in which nitrogen is applied at a nonlimiting rate) and from ramped strips in which nitrogen is applied at incrementally increasing rates on plots arranged in a strip. Two of the optical reflectance-based prediction systems are based on the nitrogen-rich strip method, which uses the nitrogen fertilizer optimization algorithm developed by Raun et al. (2002). The other two are based on the ramped strip method. One of the two nitrogen-rich strip systems accounts for the effect of parameter estimation uncertainty in making predictions, while the other does not. Similarly, only one of the two ramped strip systems accounts for parameter uncertainty. We assume a preplant nitrogen application rate of 34

kg ha^{-1} for all four systems mentioned above, and that the recommended rates from the optical reflectance-based prediction systems are applied as topdress urea-ammonium nitrate solution. It is also assumed that topdress nitrogen applications are 1.52 times as efficient as preplant applications.

The profitability of the above systems is also calculated relative to the historical extension advice to apply 90 kg ha^{-1} as preplant nitrogen. Additionally, the maximum value of a perfect nitrogen needs prediction system is calculated by estimating the profitability of two different perfect predictors based on the yield data, one of which accounts for parameter uncertainty, while the other does not.

The results indicate that given 2009 prices and assumptions about nitrogen use efficiency from midseason topdress nitrogen applications, the optimal strategy to maximize expected profit is to follow the historical extension advice. Provided anhydrous ammonia is available for preplant application, this strategy is more profitable than the most profitable optical reflectance-based prediction system by \$18.74 ha^{-1}. Although the extension advice applies an average of 22.52 kg nitrogen ha^{-1} more than the optimal rate, the unused nitrogen is applied as relatively inexpensive anhydrous ammonia, rather than urea-ammonium nitrate solution. Ultimately, the historical extension advice is more profitable than the optical reflectance-based predictors for two reasons: 1) because anhydrous ammonia is about half the price of urea-ammonium nitrate solution; and 2) because the extension advice avoids topdress application costs altogether. Results are similar when the same estimation is conducted assuming no increase in nitrogen-use efficiency from topdress relative to preplant nitrogen applications. However, when anhydrous ammonia is unavailable, and preplant nitrogen must be applied as dry urea, there are no significant differences between the extension recommendation and the optical reflectance-based predictors. This change is primarily due to the high price of urea, which is nearly double that of anhydrous ammonia.

Parameter uncertainty has an effect on the true expected profit maximizing nitrogen rate which is greater than the deterministically calculated rate by 4.73 kg ha^{-1}. However, even accounting for estimation uncertainty in the parameters of the optical reflectance-based predictors does not significantly increase their profitability relative to the extension advice. This result indicates that estimation uncertainty is relatively unimportant as a source of prediction error. Thus, other sources of prediction error should be studied further, including uncertainty about the relationship between optical reflectance measures and the true crop response function parameters.

Introduction

Long-term experiments conducted on the Magruder plots in Stillwater, Oklahoma have shown that application of nitrogen fertilizer (N)—either from commercial sources or from manure—can increase yields of hard red winter wheat by between 150% and 300% as compared to the check plot, on which no N has been applied for more than 100 years (Edmeades, 2003). These and other long-term trials have shown that N application can significantly increase yields and profits. For instance, based on a long-term trial at Lahoma, Oklahoma—and based on observation of actual farmer behavior—the Oklahoma Cooperative Extension Service has historically recommended applying 0.033 kg N ha^{-1} per kg of yield goal for winter wheat (Arnall, Edwards and Godsey, 2008). Commercial nitrogen fertilizer (N) is an essential element of crop agriculture, accounting for approximately 28% of annual operating expenditures for winter wheat cultivation (United States Department of Agriculture, 2005). Additionally, research shows that applied commercial N accounts for between 40% and 60% of food output in the United States (Stewart et al., 2005).

Raun and Johnson (1999) estimate that 67% of applied N is lost through leaching, runoff, and volatilization because application does not correspond to plant needs either spatially or temporally. In effect, an average of 67% of N expenditures is not recovered in grain. Improved nitrogen-use efficiency (NUE) not only offers increased producer profits but also environmental benefits, such as reduction of eutrophication in the Gulf of Mexico and decreased emissions of nitrous oxide, a powerful greenhouse gas (see Bongiovanni and Lowenberg-DeBoer, 2004; Faeth and Greenhalgh, 2000; Scavia, Justić and Bierman, 2004). To address the need for improved NUE, Raun et al. (2002) developed a nitrogen fertilizer optimization algorithm (NFOA). This algorithm is used to predict the uniform N application rate that will maximize NUE so that farmers can avoid applying unnecessary N that cannot be recovered by the crop. The NFOA uses midseason optical reflectance imaging (ORI) data from a N-rich strip (NRS) applied prior to planting, as well as from an untreated adjacent strip on which the producer may or may not have applied some preplant N. The whole-field NRS system strives to maximize NUE without reducing crop yields, thereby enabling producers to avoid unnecessary N expenditures while maintaining or even increasing yields. Whole-field N requirements predictors like the NRS system should be particularly useful in areas where within-field variability of N requirements is low.

Two different whole-field N requirement prediction systems are in use for winter wheat in Oklahoma, including the aforementioned NRS system, as well as a ramped strip (RS) system using small experimental plots arranged in strips with incrementally increasing N application rates (Arnall, Edwards and Godsey, 2008). Both systems assume that grain yield is a function of the most limiting input, so that yield responds linearly to N application until the crop response ceases due to other constraining variables, such as rainfall. Using in-season ORI measures from the NRS or the ramped strip, each system predicts the midseason topdress N application rate at which yield will reach a plateau.

Why might the NRS and RS systems make different predictions of the optimal N rate for any given site-year? The answer lies in the assumptions made by the different prediction systems. Both assume the yield intercept and the yield plateau vary between sites and across years. The NRS system uses only data from the untreated strip (or farmer pre-plant rate) and the non-limiting NRS in the NFOA developed by Raun et al. (2002). The NFOA assumes a site-year invariant crop response to topdress N, based on the percent N in grain and the average NUE for topdress N applications. If the restriction on the slope imposed by the NFOA is accurate, the NRS approach could be superior to the RS system. However, if crop N response varies significantly between site-years, the RS approach may be superior because it actually estimates the slope of the N response.[3] Raun et al. (2005) indicate that NUE for a topdress N application is between 50% and 70%, but NUE is not constant across time and space, as shown by Arnall et al. (2009).

[3] In this paper, data used to approximate recommendations from the NRS and RS come from randomized experimental plots that differ from the actual strips used in practice in terms of size and the number of N treatment rates used. Thus, the approach used here could under- or overestimate the accuracy of the two approaches. Additionally, because all data used are based on preplant N applications, we are forced to assume that crop response to topdress N is proportional to preplant N response. This could potentially bias our results in favor of the ramped strip method.

Based on the LRP functional form, underestimating (overestimating) NUE for a particular site-year will lead to an N requirement prediction that is greater (less) than the true optimal topdress N application. Arnall et al. (2009) show that NUE for a preplant N application can be predicted based on the response of ORI measures to N application. They point out that NUE depends upon a number of variable factors—e.g., temperature and rainfall—which can have an impact on N mineralization and volatilization. Thus, midseason applications can reasonably be expected not only to increase NUE by reducing early season N losses but also to reduce variability of NUE across time by attenuating early-season interaction between N fertilizer and climatic variables.

Inclusion of parameter uncertainty in the prediction processes for the NRS and RS systems might also lead to changes in predicted optimal N application rates. Babcock (1992) examines "explanations for farmers 'over-applying' nitrogen fertilizer," despite the increase in yield variability associated with N fertilizer. Babcock discusses several sources and types of uncertainty, including "estimation uncertainty," or the uncertainty inherent in any estimated relationship, such as a yield-response function. He indicates that uncertainty can also arise due to misspecification of functional form, weather, and the unknown amount of N present in the soil at the time of N application. Babcock also discusses specifically the linear response-plateau (LRP) functional form (which is assumed by the NRS and RS prediction systems). He finds that when the plateau is considered uncertain (while the slope and intercept of the LRP function remain constant), producers will increase N applications relative to the deterministically calculated optimum if marginal revenue when N is binding is more than twice the price of N. Past literature supports the use of functional forms derived from the von Liebig hypothesis to model agricultural production (e.g., Paris and Knapp, 1989; Berck and Helfand, 1990; Paris, 1992; Chambers and Lichtenberg, 1996). Tembo et al. (2008) model uncertainty and expected profit maximization when the crop response plateau varies randomly by site or year. The analysis presented in this paper considers estimation uncertainty about *all* parameters of the LRP functional form, rather than only the plateau, and uses Monte Carlo integration to solve for the expected profit maximizing level of N application. To date, uncertainty inherent in parameter estimation has not been fully considered for the LRP functional form, though such estimation uncertainty may have substantial effects on maximization of expected profits because the model is nonlinear.

Historical evidence shows that unambiguously profitable agricultural innovations are typically adopted rapidly, as was the widespread use of commercial N fertilizer in the early Twentieth Century. Glyphosate tolerant soybeans were shown early on to be profitable compared to conventional seed (Roberts, Pendergrass and Hayes, 1999), and were speedily adopted by producers—increasing from zero to more than 85% of U.S. soybeans acres between 1996 and 2006 (Castle, Wu and McElroy, 2006). Other innovations have not been so widely adopted, such as annual soil testing, which takes place on less than 10% of agricultural land in Oklahoma (Raun et al., 2005). The use of NRS and RS N requirement predictors has also faced slow adoption, implying that these technologies may not be profitable in all cases. Biermacher et al. (2006) determined, based on yield data from long-term trials at Lahoma and Altus, Oklahoma, that the maximum possible benefit of a sensor-based precise N application system is between \$22 and \$31 ha^{-1}, relative to the conventional 90 kg N ha^{-1}. Biermacher et al. (2009) found that use of the NFOA with actual ORI data from growing plants was less profitable than applying 45 kg ha^{-1} as preplant anhydrous ammonia (NH_3). Their results indicate that the NFOA effectively determines whether plants are suffering from N stress, but that recommended midseason application rates from the NFOA may be too low when plant are suffering N stress. The conclusion to be drawn from Biermacher et al. (2006) and Biermacher et al. (2008) is that optical sensing methods have the potential to bring about large increases in profit, but that the NFOA requires significant adjustment to improve its accuracy as a N requirements predictor.

The objectives of this study are to determine 1) whether NUE for preplant N varies by site-year, 2) whether either the RS or NRS technology is unambiguously more profitable than applying 90 kg ha^{-1} preplant, and 3) whether inclusion of parameter uncertainty improves the predictive capacities of the NRS and/or RS technologies. This paper estimates the relative profitability of the following seven whole-field prediction systems:

1) a "perfect predictor" system that uses the production function estimated from actual yields and in each site-year in conjunction with the deterministic or "plug-in" method to determine the optimal rate of topdress N (hereafter called PPD),
2) a "perfect predictor" that uses the same production function as in system (1) above, but accounts for uncertainty about the estimates of the production function parameters (hereafter called PPU) to determine the optimal topdress N rate,
3) the RS system described above (hereafter called RSD),
4) a modified version of the RS systems that accounts for uncertainty about yield given no top-dress treatment, maximum possible yield, and the rate at which yield responds to additional N application (hereafter called the RSU system),

5) the NRS system (hereafter called NRSD) described in Raun et al. (2002),
6) a modified version of the aforementioned NRS system that accounts for uncertainty about the estimated maximum possible yield, as well as the yield given no top-dress treatment (hereafter called the NRSU system), and
7) the historical extension recommendation (hereafter referred to as the ER system) of 90 kg N ha^{-1} from anhydrous ammonia (NH_3) prior to planting, based on a yield goal of 2727 kg ha^{-1}.

N is assumed to be applied as anhydrous ammonia (NH_3) at 34 kg ha^{-1} prior to planting to avoid early season N stress (Arnall, Edwards and Godsey, 2008). The ORI-based systems then are used to predict how much additional N (if any) should be applied as topdress UAN. The results will inform further development of methods to predict economically optimal crop N requirements using midseason ORI data, and determine (given these assumptions) whether one of the five ORI-based methods should be recommended to producers over the others.

Theory

A producer's goal is to maximize expected profit by choosing one of the five alternative N application rate prediction systems. This problem can be expressed mathematically as follows:

(1) $$\max_k E[\pi_k(y(N_k, T_k) | T_k = F_k(\phi_k))]$$

where π_k is the profit from system *k*; y is yield, N_k is the amount of preplant N applied by system *k*; T_k is the amount of topdress N applied by system *k*; F_k is a function used by system *k* to make the N requirement prediction; ϕ_k is the information set used by system *k*; and $k = PPD, PPU, NRSD, NRSU, ER$. Thus, the profit maximizing producer will choose the strategy with the highest expected profit. Here, the expected return for each of the five methods is:

(2) $$E(\pi_k) = p_c E[y(N_k, T_k)] - p_{pn} N_k - p_T T_k - \delta_k p_{aT} - p_{fk}$$

where p_c is the price of the crop, p_{pn} is the price of pre-plant N, p_T is the price of topdress N, δ_k is a binary variable that indicates $T_k > 0$; p_{aT} is the custom application cost for topdress N; and p_{fk} is the fixed cost of using method *k*, including the cost of creating and analyzing an experimental strip, as well as the acquisition and custom application costs for preplant N required by method *k*.

Data

The data for this study come from experiments conducted at ten sites located throughout the state of Oklahoma between 1998 and 2008. The ten sites are located at the Efaw, Haskell, Hennessey, Lahoma, Lake Carl Blackwell, Perkins, Stillwater, and Tipton agricultural experiment stations. Table II-1 contains the specifics about N treatment levels, replications, soil types, and dates for each experimental location, while the map in figure II-1 shows the locations of the experimental sites. Each site had at least three different levels of N treatment, which differed by site, and occasionally between years at the same site. The number of replications at each N application rate varies by site-year. ORI measures for each observation were collected around Feekes growth stage 5, and yield was measured at harvest. These data are used to provide application recommendations based on the RSD, RSU, NRSD, and NRSU systems.

Table II-1. Locations, Years, Soil Types, and Nitrogen Levels, and Replications for Experiments

Experiment Station	Years	Soil Type	Nitrogen Treatment Levels (kg ha^{-1})					
Efaw 1	1999-2006	Easpur loam	0 (3)	45 (3)	90 (3)	179 (3)	269 (3)	538[a] (3)[b]
Efaw 2	1999-2003	Easpur loam	0 (3)	56 (6)	90 (6)	123 (6)		
Haskell	1999-2002	Taloka silt loam	0 (8)	112 (16)	168 (4)			
Hennessey	2000-2003	Shellabarger sandy loam	0 (3)	56 (5)	90 (6)	123 (6)		
Lahoma	1999-2008	Grant silt loam	0 (8)	22 (4)	45 (4)	67 (4)	90 (4)	112 (4)
Lake C.B.	2004, 2006	Port silt loam	0 (4)	50 (4)	100 (4)			
Perkins 1[c]	1998-2006	Teller sandy loam	0 (3)	56 (3)	112 (3)	168 (3)		
Perkins 2	1998	Teller sandy loam	0 (9)	56 (9)	112 (9)	168 (9)		
Stillwater	1999-2006, 2008	Norge silt loam	0 (8)	45 (4)	90 (4)	134[d] (4)		
Tipton	1998	Tipton silt loam	0 (12)	56 (12)	112 (12)	168 (12)		

[a] Rate not available in 2000.
[b] Numbers in parentheses are the number of replications at each rate each year.
[c] Numbers of replications are the same in 1998 as at Perkins 2.
[d] Rate not available in 2004, 2005, 2008.

The NRS is the area of each site on which the maximum N rate was applied. The ramped strips here are approximated by the different levels of N applied on randomized plots. The prototype ramped strip applicator that has been developed typically applies more different levels of N than available in this dataset, but there is no theoretical advantage to having more than three design points, given two treatment levels are on the slope and one is on the plateau (Richter and Brorsen, 2008). Note also that the Efaw 2, Hennessey, and Lahoma experiments do not include a rate that equals or exceeds the maximum N rate that would be applied to the NRS or RS. The Stillwater experiment also

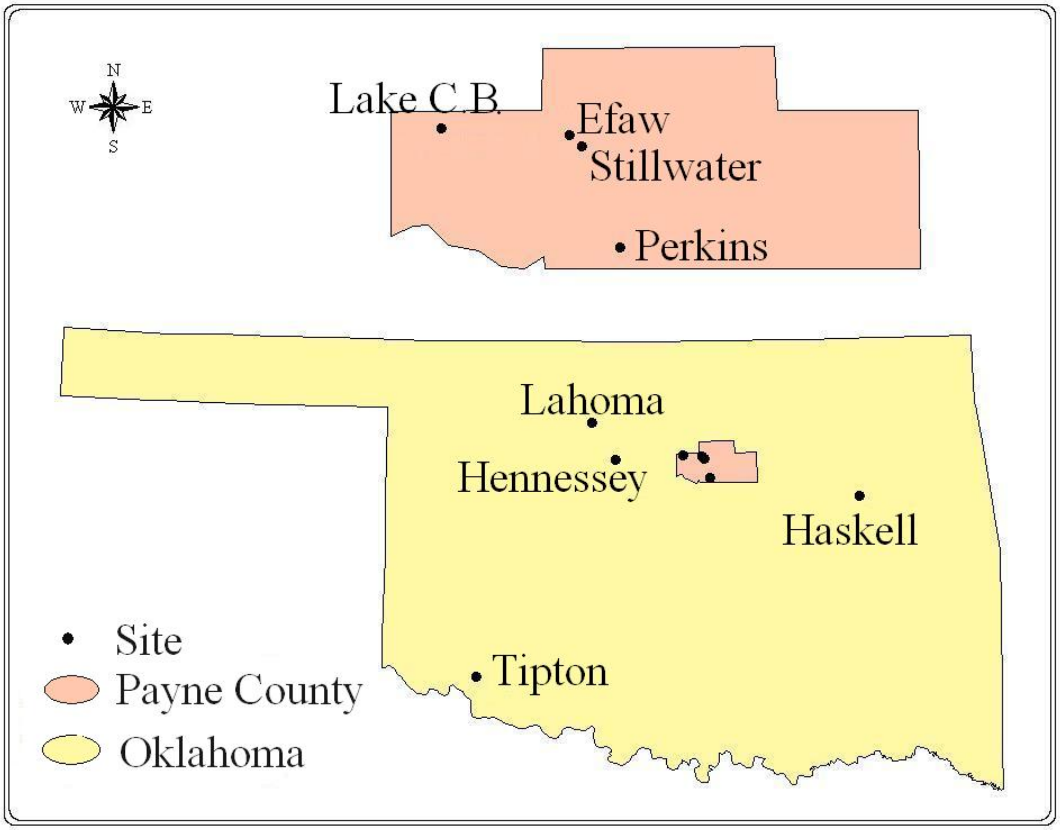

Figure II-1. Map of experimental locations.

suffers from the same issue in 2004, 2005, and 2008. Thus, in these instances, estimates of the plateau yield may be biased downward due to lack of treatment levels high enough to reach the plateau. However, this limitation does not affect the analysis of the relative profitability of the five N needs prediction methods because all prediction systems will suffer from the same constraint on the plateau yield estimation in any given site-year.

In sample bias may also cause overestimation of the accuracy of the predictive systems because both predicted and actual estimates of the production functions must be made based on data from the same observations. This means that the data will not capture the variability of N response that might be found within an entire field. Also, the data come from small plots relative to the entire field. A large NRS would actually capture more within-field variability than is represented by the plots in these data, as would a large RS. Also, the mechanism used for optical reflectance sensing may be important. Readings from a small handheld sensor might not capture as much variability as readings from an array of sensors, again under-representing within field variability. Conversely, use of a handheld sensor might increase measurement error in NDVI data.

Based on local cooperative prices on February 14, 2009, this paper assumes N from UAN 28-0-0 costs \$1.10 kg^{-1}, N from urea costs \$0.99 kg^{-1}, and N from anhydrous ammonia (NH_3) costs \$0.57 kg^{-1}. Custom application costs for UAN are assumed to be \$9.71 ha^{-1}, custom application for dry urea is priced at \$9.19 ha^{-1}, and custom application of NH_3 is 20.49 ha^{-1} (Doye, Sahs and Kletke, 2007). The wheat price is \$0.24 kg^{-1}.

The dimensions of the NRS are assumed to be 19.8 m by 803 m (1.59 ha), and the non-limiting N application rate (from NH_3) is 134 kg ha^{-1}. It is assumed the NRS is custom-applied simultaneously with 34 kg N ha^{-1} preplant N, and thus the NRS simply requires an extra pass over the center of the field applying an additional 100 kg N ha^{-1}. The cost of using the NRS includes the extra cost of NH_3 for application to the NRS, custom application costs of NH_3 for the NRS, 1.5 hours of producer labor to read the NRS, and the cost of the sensor. A GreenSeeker® and PDA can be acquired from NTech Industries for \$4,995.00. Assuming a 5-year useful life for the sensor and PDA, a depreciation rate of 20%, a 1,000 ha farm, and a 63 ha field, the cost of owning and operating the sensor is \$1.00 ha^{-1} yr^{-1}. The total cost of a NRS is \$212.07 per field, or \$3.37 ha^{-1}. Table II-2 contains a partial budget for the creation of a NRS.

The RS is typically applied early after planting as top-dress UAN 28-0-0. Producers are advised to apply 3 strips per field, each measuring 3 m by 55 m (0.0165

Table II-2. Partial Budget for Creation and Use of a Nitrogen-Rich Strip on a 63 ha Field

Operating Input:	Units	Price	Quantity	Cost
NH_3	kg	0.57	160.00	91.20
NH_3 Application	ha	20.49	1.59	32.58
Sensor	ha	1.00	63.00	63.00
Producer Labor	hr	17.50	1.50	20.25
Total Cost of NRS	field			207.03
Total Cost of NRS	ha			3.29

Table II-3. Partial Budget for Creation and Use of Three Ramped Strips on a 63 ha Field

Operating Input	Units	Price	Quantity	Cost
UAN	Kg	1.10	3.31	3.64
Road Time	\$ km^{-1}	4.12	8	32.96
Coop Labor	\$ hr^{-1}	17.50	2.50	43.75
Sensor	\$ ha^{-1}	1.00	63.00	63.00
Producer Labor	\$ hr^{-1}	17.50	2.50	43.75
Total Cost of RS	\$ field^{-1}			187.10
Total Cost of RS	\$ ha^{-1}			2.97

ha), starting at an application rate of 0 kg ha^{-1}, and increasing the application rate in increments of 14.56 kg ha^{-1}, until reaching the maximum rate that could possibly be used by the plants (assumed to be 134 kg ha^{-1}). Thus, the average N application rate in the RS is 67 kg ha^{-1}. Because the RS is applied separately from pre-plant N, it is assumed the producer pays road time totaling eight km per field at \$4.12 km^{-1} for delivery of the RS applicator. It is assumed that the custom application of a RS takes 2.5 hours of custom labor, and that the producer later spends 2.5 hours reading the three strips with his own Greenseeker® sensor and PDA. Thus, the total cost of a RS is \$187.10 per field, or \$2.97 ha^{-1}. Table II-3 is a partial budget for the creation and use of a RS.

In the baseline case, midseason topdress UAN is assumed to be more efficient than preplant NH_3 or early-season UAN. In-field use of the RS method assumes the plateau application rate found in the RS can be multiplied by the ratio of preplant N use efficiency (NUE) to topdress NUE. This ratio is 0.33/0.5 = 0.66 (Solie, 2009). Multiplying the preplant plateau application rate by this ratio is equivalent to multiplying the response when N is limiting by 1.52—i.e, topdress N is 1.52 times more efficient.

Procedures

Space-Time Variability of Crop Response

One question germane to any ORI-based midseason N requirement prediction system is how much crop N response varies across time and space. The findings of Arnall et al. (2009) indicate that NUE for preplant N is variable. However, they do not specifically quantify this variability. This is done by estimating the following model:

(3) $$y_{it} = \min\{\alpha + v_t + (\beta + \upsilon_t)N_{it}, P + v_t + \omega_t\} + \varepsilon_{it}$$

where y_{it} is yield on plot *i* in site-year *t*; α is the intercept yield; v_t is a random effect shifting the intercept for site-year *t*; β is the slope of N response; υ_t is a random effect that changes the slope of N response for site-year *t*; N_{it} is the amount of preplant N applied on plot *i* in site-year *t*; P is the plateau yield; ω_t is a random effect on the plateau for site-year *t*; ε_{it} is a random disturbance for plot *i* in site-year *t*; and v_t, υ_t, ω_t, and ε_{it} are assumed to be distributed normally and independently, with respective means zero, and variances σ_v^2, σ_υ^2, σ_ω^2, and σ_ε^2, respectively. A restricted model is also estimated in which the slope of N response does not vary across site-years—i.e., $\sigma_\upsilon^2 = 0$ —and use a likelihood ratio test to determine whether this restriction is true. The estimated mean slope β and variance σ_{υ}^{2} are then used to generate a 95% confidence interval for N response (and NUE) for preplant applications across all site-years.

Expected Profit Maximizing Application Rates from Perfect Predictors

In addition to estimating the relative profitability of the NRSD, NRSU, RSD, and RSU prediction methods, the profitability of each ORI-based system is calculated relative to two “perfect predictors” so that the component costs and revenues can be compared across the systems. This process begins with estimation of the yield response function for each site-year in PROC NLMIXED in SAS as follows:

(4) $$y_{it} = \min\{\alpha_{0t} + \beta_{0t} N_{it}, P_{0t}\} + \varepsilon_{it},$$

where y_{it} is yield on plot *i* in site-year *t*; α_{0t} is the intercept yield for site-year *t* given no preplant N application; β_{0t} is the yield response to preplant N for site-year *t* when N is non-limiting; N_{it} is the pre-plant N application rate on plot *i* in site-year *t*; P_{0t} is the plateau yield for site-year *t*; and ε_{it} is a normally distributed disturbance with a variance specific to site-year *t*.

To account for uncertainty about the estimated parameters of the production function for each site-year, Monte Carlo simulation is used to generate ten thousand observations from the multivariate-normal distribution of the parameter estimates from equation (4). Each observation is generated as follows:

(5) $$\hat{\boldsymbol{\beta}}_{0jt} = \hat{\boldsymbol{\beta}}_{0t} + \mathbf{Q}_{0t}'\mathbf{z}_{j}\text{, such that } \mathbf{Q}_{0t}\mathbf{Q}_{0t}' = \boldsymbol{\Omega}_{0t}$$

where $\hat{\boldsymbol{\beta}}_{0jt}$ is the j^{th} simulated 3 by 1 vector of parameter estimates for site-year *t*; $\hat{\boldsymbol{\beta}}_{0t}$ is the 3 by 1 vector of parameter estimates for site-year *t* from equation (4), $\mathbf{Q}_{0t}'$ is the 4 by

4 lower triangular Cholesky decomposition of $\mathbf{\Omega}_{0t}$, which is the 3 by 3 covariance matrix of the parameters estimated in equation (4); $\mathbf{z}_j$ is the j^{th} 3 by 1 vector of randomly generated deviates from a standard normal distribution; $j = 1, \ldots, J$; J equals ten thousand; and the 0 subscript indicates that the parameters are estimated based on pre-plant N response. Occasionally, a standard error cannot be estimated for either the slope or plateau of the production function for a site-year due to data limitations. In such cases, the parameter is considered a constant, and the other parameters are used for the Monte Carlo simulation. Such estimation problems are discussed further in the results and conclusions sections.

To estimate the expected profit maximizing topdress N application rate, parameters estimated and simulated in equations (4) and (5) must be adjusted because a) it is assumed that all prediction systems apply 34 kg N ha^{-1} as preplant NH_3, and b) it is also assumed that the marginal product of midseason topdress UAN is 1.52 times that of preplant NH_3 due to an increase in NUE. To account for the aforementioned assumptions, the following adjustments are made based on the vector $\hat{\boldsymbol{\beta}}_{0jt}$:

(6) $$\hat{\alpha}_{1jt} = \max(\min(\hat{\alpha}_{0jt} + \hat{\beta}_{0it}34, \hat{P}_{0jt}), \hat{\alpha}_{0jt}), \text{ and}$$

(7) $$\hat{\beta}_{1jt} = 1.52\hat{\beta}_{0jt}$$

where $\hat{\alpha}_{1jt}$ is the j^{th} simulated yield at the pre-plant rate of 34 kg ha^{-1} in site-year *t*; $\hat{\alpha}_{0jt}$ is the j^{th} simulated yield when no N is applied in site-year *t*; $\hat{\beta}_{0jt}$ is the j^{th} simulated N response to pre-plant NH_3 for site-year *t*; $\hat{P}_{0jt}$ is the j^{th} simulated plateau-yield in site-year *t*; and $\hat{\beta}_{1jt}$ is the j^{th} simulated response to midseason topdress UAN for site-year *t*;

$j = 1, \ldots, J$; and J equals ten thousand. The max and min functions in equation (6) prevent predicted yield at 34 kg N ha^{-1} from being greater than the plateau yield or less than the intercept when no N is applied. These restrictions impose the constraints that yield can never be higher than the plateau yield and that slope of the LRP function is always greater than or equal to zero.

Parameter estimates of the average yield given 34 kg ha^{-1} of preplant N from NH_3, and for the yield response to topdress UAN for site-year t ($\hat{\alpha}_{1t}$ and $\hat{\beta}_{1t}$, respectively) are found by taking the means of $\hat{\alpha}_{1jt}$ and $\hat{\beta}_{1jt}$ from equations (6) and (7). These parameter estimates are used in conjunction with the site-year production function estimates from equation (4) to determine the optimal topdress UAN application rate using the deterministic PPU method. This rate is found using the formula:[4]

$$(8) \qquad T_t^D = \begin{cases} (\hat{P}_{0t} - \hat{\alpha}_{1t}) \big/ \hat{\beta}_{1t} & \text{if } p_c(\hat{P}_{0t} - \hat{\alpha}_{1t}) > (\hat{P}_{0t} - \hat{\alpha}_{1t}) \big/ \hat{\beta}_{1t} + p_{aT} \\ 0 & \text{otherwise,} \end{cases}$$

where T_t^D is the deterministically calculated PPU optimal topdress N application rate for site-year t; p_c is the price of wheat; p_{aT} is the cost of custom application of UAN; $\hat{P}_{0t}$ is the estimated plateau yield; $\hat{\alpha}_{1t}$ is the estimated yield at 34 kg ha^{-1} pre-plant NH_3; $\hat{\beta}_{1t}$ is the estimated response to topdress UAN; and the D superscript means that the N application rate is calculated using the deterministic method. Recall, however, that Babcock (1992) points out that when the plateau is uncertain, this deterministic method of solving for expected profit maximizing N rate is inadequate in the case of the LRP functions because the functional form is non-linear in parameters. Here, estimation

[4] Note that when determining the actual or predicted expected profit maximizing topdress N application rate, no information about expenditures on preplant N is needed.

uncertainty in the estimated intercept and slope for each site-year are considered in addition to uncertainty of the plateau yield.

To account for estimation uncertainty in the parameters, a nonlinear programming problem is formulated and solved to maximize expected profit from topdress UAN application for each site-year based on the Monte Carlo observations generated from equations (4), (5), (6) and (7). The maximization problem to solve for the PPU rate is:

$$\text{(9)} \qquad \max_{T_t^U} E[\pi(T_t^U)] = \sum_{j=1}^{J} \frac{p_c \min(\hat{\alpha}_{1jt} + \hat{\beta}_{1jt} T_t^U, \hat{P}_{0jt})}{J} - p_T T_t^U - p_{aT} \delta_t$$

s.t.

$$0 \le T_t^U \le 120$$

where π is return above topdress N costs ; T_t^U is the expected profit maximizing rate of topdress N application from UAN in site-year *t*, accounting for parameter uncertainty; p_c is the price of wheat; p_T is the price of UAN; δ_t is a binary variable that equals one if $T_t^U > 0$, and zero otherwise; the *U* superscript indicates that the solution accounts for parameter uncertainty; and all other symbols are previously defined. The solutions are obtained using PROC NLP in SAS.

Predicted Expected Profit Maximizing Application Rates from Ramped Strip Predictors

To predict expected profit maximizing N application rates based on the RSD and RSU methods, ORI data must first be converted to expected yields, commonly called "yield potential" in the literature (Raun et al., 2002, 2005). This conversion is needed because the ORI data are not directly comparable to yield data in terms of estimating (or predicting) yield response. The equation used to make this conversion is:

(10) $$E(y_{it}) = yp_{it} = 590.00\exp(258.20 insey_{it})$$

where y_{it} is yield on plot *i* in site-year *t*; yp_{it} yield potential on plot *i* in site-year *t*; $insey_{it}$ is the ORI measure from plot *i* in site-year *t*; and 590.00 and 258.20 are the parameters used by the NFOA (Raun, 2008). Once this conversion of ORI data has been completed, predicted yield response functions are estimated for each site-year following the estimation and simulation procedures in equations (4), (5), (6) and (7), but substituting expected yields from equation (10) as the dependent variable. Then for each site-year, the expected profit maximizing UAN application rate based on the RSD method is calculated as in equation (8), and the predicted optimal rate based on the RSU method is calculated as in equation (9), but using the predicted, rather than actual, estimates of the N response production functions for each site-year.

Predicted Expected Profit Maximizing Application Rates from

Nitrogen Rich Strip Predictors

The information set and the function used to predict the expected profit maximizing topdress N application rate based on an NRS is different from that used by the RSD and RSU systems. The NRS is used in conjunction with a check strip, where the producer has applied some amount of preplant N (assumed to be 34 kg ha^{-1}). Additionally, methods that use an NRS assume that the slope of the N response is constant across time and space.

Producers are also assumed to apply 34 kg N ha^{-1} as pre-plant NH_3. However, none of the experimental sites in the dataset include a preplant rate of 34 kg ha^{-1}, so the

ORI measure that *would* have been collected for each site-year must be predicted, given the assumed preplant rate. This is done by first estimating the function:

$$insey_{it} = \min[\alpha_t + \beta_t N_{it}, P_t] + \varepsilon_{it}, \tag{11}$$

where $insey_{it}$ is the ORI measure on plot *i* in site-year *t*; α_t is the intercept of ORI for site-year *t* given no preplant N application; β_t is the response of ORI measures to preplant N for site-year *t*; N_{it} is the amount of preplant N applied on plot *i* in site-year *t*; P_t is the ORI plateau for site-year *t*; and ε_{it} is a normally distributed random error term with a variance specific to site-year *t*.

Next, the average ORI from the farmer practice check strip is estimated using Monte Carlo simulation. Ten thousand Monte Carlo observations based on the parameters of equation (11) are generated by the following process:

$$\hat{\boldsymbol{\beta}}_{0kt} = \hat{\boldsymbol{\beta}}_{0t} + \mathbf{Q}_{0t}'\mathbf{z}_k \text{, such that } \mathbf{Q}_{0t}\mathbf{Q}_{0t}' = \boldsymbol{\Omega}_{0t}, \tag{12}$$

where $\hat{\boldsymbol{\beta}}_{0kt}$ is the k^{th} simulated 4 by 1 vector of parameter estimates for site-year *t*; $\hat{\boldsymbol{\beta}}_{0t}$ is the 4 by 1 vector of parameter estimates for site-year *t* from equation (11), $\mathbf{Q}_{0t}'$ is the 4 by 4 lower triangular Cholesky decomposition of $\boldsymbol{\Omega}_{0t}$, which is the 4 by 4 covariance matrix of the parameters estimated in equation (11); $\mathbf{z}_k$ is the k^{th} 4 by 1 vector of randomly generated deviates from a standard normal distribution; $k = 1, \ldots, K$; K equals ten thousand; and the 0 subscript indicates that the parameters are estimated based on preplant N response. The average ORI measure given the farmer practice of applying 34 kg N ha^{-1} as anhydrous ammonia is then predicted as:

$$insey_t^{FP} = \frac{insey_{kt}^{FP}}{K} = \frac{\max[\min[\hat{\alpha}_{0kt} + 34\hat{\beta}_{0kt}, \hat{P}_{0kt}], \hat{\alpha}_{0kt}]}{K} \tag{13}$$

where $insey_t^{FP}$ is the predicted average ORI measure given 34 kg N ha^{-1} preplant in site-year t; $insey_{kt}^{FP}$ is the k^{th} simulated ORI measure for site-year t; $\hat{\alpha}_{0kt}$, $\hat{\beta}_{0kt}$, $\hat{P}_{0kt}$ are the first three elements of the vector $\hat{\boldsymbol{\beta}}_{0kt}$ from equation (12); and the max and min functions ensure that the mean farmer practice ORI measure is no greater than the mean plateau ORI measure. The simulated standard error of $insey_t^{FP}$ is the standard deviation of $insey_{kt}^{FP}$. Yield potential (or expected yield) at the farmer practice level of N application is then calculated for each site-year as:

$$(14) \qquad yp_t^{FP} = 590.00\exp(258.20\,\mathrm{insey}_t^{FP}),$$

where yp_t^{FP} is the expected yield at the rate of 34 kg N ha^{-1} preplant for site-year t; $insey_t^{FP}$ comes from equation (13); and the parameters of equation (14) are the same as in equation (10).

The average ORI measure from the NRS is estimated using only the ORI data from plots where the maximum preplant N rate was applied in each site-year. Thus, the ORI measure from the NRS for each site-year is estimated as:

$$(15) \qquad insey_{it}^{MAX} = \mu_t + \varepsilon_{it},$$

where $insey_{it}^{MAX}$ is the ORI reading for plot i at the maximum preplant rate applied in site-year t; μ_t is the mean of the ORI measures at the maximum preplant application rate applied in site-year t; and ε_{it} is a normally distributed stochastic disturbance for plot i in site-year t. Based on equation (15) the average ORI measure from the NRS is:

$$(16) \qquad insey_t^{MAX} = \hat{\mu}_t,$$

where $\hat{\mu}_t$ is simply the point estimator of the mean of ORI measures at the maximum preplant N application rate applied in site-year *t*. The estimated yield potential for the NRS is calculated as:

$$(17) \qquad yp_t^{MAX} = \min[\max(yp_t^{FP}, yp_t^{FP} RI_t^{adj}), 7000],$$

where yp_t^{MAX} is the mean yield potential for the NRS in site-year *t*; 7,000 kg ha^{-1} is assumed to be the maximum possible plateau yield for winter wheat in Oklahoma (Raun et al., 2005); yp_t^{FP} is the mean yield potential for the farmer practice check strip; and RI_t^{adj} is an *adjusted* response index based on the response index used by Raun et al. (2005). Raun (2008) indicates that RI_t^{adj} is calculated as:

$$(18) \qquad RI_t^{adj} = 1.69(insey_t^{MAX} / insey_t^{FP}) - 0.70 .$$

The predicted expected profit maximizing UAN application rate prescribed by the NRSD method is then calculated based on the NFOA described by Raun et al. (2002, 2005) using the equation:

$$(19) \qquad T_t^D = \begin{cases} (yp_t^{MAX} - yp_t^{FP}) \Big/ \dfrac{0.5}{0.0239} & \text{if } p_c(yp_t^{MAX} - yp_t^{FP}) > (yp_t^{MAX} - yp_t^{FP}) \Big/ \dfrac{0.5}{0.0239} + p_{aT} \\ 0 & \text{otherwise,} \end{cases}$$

where T_t^D is the NRSD predicted expected profit maximizing topdress UAN application rate; yp_t^{MAX} is the yield potential estimate for the NRS in site-year *t* from equation (17); yp_t^{FP} is the estimated yield potential at 34 kg N ha^{-1} pre-plant for site-year *t* from equation (14); 0.5 is the expected NUE from a midseason topdress UAN application (Raun et al., 2005); 0.0239 is the percentage of N in the grain multiplied by a conversion constant (Raun et al., 2005). Note that the NFOA assumes a constant slope of 20.92 kg wheat ha^{-1} for an increase of 1 kg N ha^{-1} in the topdress N application rate—i.e., $0.5/0.0239$.

To determine the effects of parameter uncertainty on expected profit maximization—i.e., to obtain predictions for the NRSU method—the variances of yp_t^{FP} and yp_t^{MAX} must be accounted for, as well as the covariance between them. In practice, the covariance between yp_t^{FP} and yp_t^{MAX} for a particular site-year would not be known because the two parameters (yp_t^{FP} and yp_t^{MAX}) are not estimated jointly in a single equation. To determine a plausible covariance that can be assumed for all field years, the following model is estimated:[5]

(20) $$insey_{it} = \min[\alpha + \beta N_{it}, P] + \varepsilon_{it},$$

where $insey_{it}$ is the ORI measure on plot *i* in site-year *t*; α is the intercept ORI measure; β is the response of ORI measures to preplant N application; N_{it} is the amount of preplant N applied on plot *i* in site-year *t*; P is the plateau ORI measure; and ε_{it} is a normally distributed error term with mean zero and variance σ_ε^2. Ten thousand Monte Carlo observations for each site-year on $insey_t^{FP}$ and $insey_t^{MAX}$ are then created following the process:

(21) $$\begin{bmatrix} insey_{jt}^{FP} \\ insey_{jt}^{MAX} \end{bmatrix} = \begin{bmatrix} insey_t^{FP} \\ insey_t^{MAX} \end{bmatrix} + \mathbf{Q}_t^{'}\mathbf{z}_j \text{, such that } \mathbf{Q}_t\mathbf{Q}_t^{'} = \mathbf{\Omega}_t \text{ and } \mathbf{\Omega}_t = \begin{bmatrix} \sigma_{FPt}^2 & \sigma_{\hat{\alpha},\hat{P}} \\ \sigma_{\hat{\alpha},\hat{P}} & \sigma_{MAXt}^2 \end{bmatrix}$$

[5] Because equation (20) is used only to estimate the covariance of the intercept and plateau estimates, the resulting parameter estimates are not presented in this work. Suffice it to say the estimated covariance ($\sigma_{\hat{\alpha},\hat{P}}$) is -1.16E-15.

where $insey_{jt}^{FP}$ is the j^{th} simulated observation of the ORI reading from the farmer practice in site-year *t*; $insey_{jt}^{MAX}$ is the j^{th} simulated observation of the ORI reading from the NRS in site-year *t*; $\mathbf{Q}_t^{'}$ is the 2 by 2 lower triangular Cholesky decomposition matrix; $\mathbf{z}_j$ is a 2 by 1 vector of deviates from a standard normal distribution; $\mathbf{\Omega}_t$ is the estimated covariance matrix of parameter estimates for site-year *t*; σ_{FPt} is the simulated standard error of the estimated farmer practice ORI reading for site-year *t*, which comes from equation (13); σ_{MAXt} is the standard error of the mean ORI reading from the NRS for site-year *t*, estimated in equation (16); $\sigma_{\hat{\alpha},\hat{P}}$ is the covariance between the estimated intercept and plateau parameters from equation (20); $j = 1,\ldots, J$; *J* is ten thousand; and all other symbols are as defined previously. The simulated ORI observations from equation (21) are then transformed to yield potential (or expected yield) data using the parameters from equation (10) as follows:

(22) $$yp_{jt}^{FP} = 590.00\exp(258.20 insey_{jt}^{FP}) \text{, and}$$

(23) $$yp_{jt}^{MAX} = \min[\max(yp_{jt}^{FP}, yp_{jt}^{FP} RI_{jt}^{adj}), 7000]$$

where yp_{jt}^{FP} is the j^{th} simulated observation on yield potential given a pre-plant N application rate of 34 kg ha^{-1} for site-year *t*; yp_{jt}^{MAX} is the j^{th} simulated observation on yield potential in the NRS; $RI_{jt}^{adj} = 1.69(insey_{jt}^{MAX} / insey_{jt}^{FP}) - 0.70$ is the j^{th} simulated observation on the adjusted ORI response index for site-year *t*; and all other symbols are defined as previously.

Based on this Monte Carlo simulated dataset, the following programming problem is used to predict the expected profit maximizing N rate based on the NRSU method:

$$\max_{T_t^U} E[\pi(T_t^U)] = \sum_{i=1}^{J} \frac{p_c \min(yp_{jt}^{FP} + (0.5/0.0239)T_t^U, yp_{jt}^{MAX})}{J} - p_T T_t^U - p_{aT}\delta_t \tag{24}$$

s.t.

$0 \le T_t^U \le 120$

where T_t^U is the optimal topdress N application rate predicted by the NRSU method for site-year *t*; δ_t is a binary variable equal to one if $T_t^U > 0$; and all other symbols are defined the same as previously. The NRSU predicted expected profit maximizing N application rate for each site-year is calculated based on equation (24) using PROC NLP in SAS.

Calculation of Expected Yields and Expected Returns

After solving for the expected profit maximizing and predicted expected profit maximizing N application rates for each prediction system in each site-year, differences are calculated between the systems in terms of yields, nitrogen application rates and profits. The expected yield given each predictor for each site-year is calculated as:

$$E[y(N_k, T_{kt})] = \sum_{j=1}^{J} \frac{\max[\min(\hat{\alpha}_{1jt} + \hat{\beta}_{1jt} T_{kt}, \hat{P}_{0jt}), \min(\hat{\alpha}_{0jt} + \hat{\beta}_{0jt} N_k, \hat{P}_{0jt})]}{J} \tag{25}$$

where *y* is yield; T_{kt} is the topdress N application rate prescribed by system *k* for site-year *t*; N_k is the preplant N application rate prescribed by system *k* for site-year *t*; and all other symbols are as defined in (6) and (7). Expected returns above the costs of N acquisition, application, and prediction technology (hereafter called net revenues) are calculated for each site-year as:

$$E[\pi(N_k, T_{kt})] = \sum_{j=1}^{J} \frac{p_c \max[\min(\hat{\alpha}_{1jt} + \hat{\beta}_{1jt} T_{kt}, \hat{P}_{0jt}), \min(\hat{\alpha}_{0jt} + \hat{\beta}_{0jt} N_k, \hat{P}_{0jt})]}{N} \tag{26}$$
$$- p_T T_{kt} - p_{aT} \delta_{kt} - p_{fk},$$

where δ_{kt} is a binary variable equal to one if $T_{kt} > 0$; p_{fk} is the fixed cost of using method *k*, including the costs of pre-plant N and preplant N application and (if required by system *k*) the cost of an RS or NRS; the application systems (*k*) are the PPD, PPU, RSD, RSU, NRSD, NRSU, and ER systems; and all other symbols are as defined previously.

Next, paired differences are calculated for expected profits, expected yields and total N application rates for each site-year. These calculations are:

$$D_{qkt}^{y} = E[y(N_q, T_{qt})] - E[y(N_k, T_{kt})], \qquad q \neq k \tag{27}$$

$$D_{qkt}^{\pi} = E[\pi(N_q, T_{qt})] - E[\pi(N_k, T_{kt})], \qquad q \neq k \tag{28}$$

$$D_{qkt}^{N} = (N_q + T_{qt}) - (N_k + T_{kt}), \qquad q \neq k \tag{29}$$

where D_{qkt}^{y}, D_{qkt}^{π}, and D_{qkt}^{N} are the differences of expected yields, expected returns, and total N applications between methods *q* and *k* for site-year *t*; N_q and N_k are the preplant N application rates prescribed by methods *q* and *k*, respectively; T_{kt} and T_{qt} are the topdress N applications rates prescribed by methods *q* and *k*, respectively, for site-year *t*; and *q* and *k* are 1) the PPD method, 2) the PPU method, 3) the RSD method, 4) the RSU method, 5) the NRSD method, 6) the NRSU method, or 7) the ER method of N requirement prediction.

These paired-differences are used to determine the expected differences in yields, profits, and total N application rates between the seven systems. Rather than conducting a student's *t* test, which relies on normally distributed paired differences, nonparametrically bootstrapped means and standard errors of the paired differences of yields, returns, and N application rates are used. This is done by random sampling with replacement from the original 53 site-years to create 10,000 samples of 53 site-years each, and taking the means of the sample means. A *t*-test is then applied to the bootstrapped means and standard errors to determine whether the differences between the systems are statistically significant.

The process described in the procedures section is then repeated to determine how sensitive the results are to changes in assumptions. One alternative scenario assumes that all preplant N must come from dry urea, rather than from NH_3, while in the other scenario assumes there is no increase in NUE from a topdress N application relative to a preplant application.

Results

The parameter estimates from equation (3) are presented in table II-4. The unrestricted model allows crop N response to vary across site-years, while the restricted model assumes N response is invariant to site-year. The likelihood ratio statistic to test this restriction is $LR = -2(-9041.5 + 9069.00) = 27.5$, which exceeds the chi-square critical value with one degree of freedom at the 0.01 significance level (6.64). The null hypothesis can thus be rejected, leading to the conclusion that the rate at which winter wheat responds to preplant N varies significantly by site-year. The estimated slope parameter is 13.28 kg wheat per kg N, and the variance of site-year random effects on the slope is 89.88; thus the 95% confidence interval for the expected slope for any given site-year is $10.53 < \beta_t < 16.02$, where β_t is the slope of N response for site-year *t*. The implication of this result is that the assumption of a constant slope for all site-years may cause prediction error when using the NFOA to predict optimal topdress N application rates. However, crop response to *topdress* N may be less variable than that estimated here because N applied midseason is less likely to be lost to volatilization or runoff before it can be used by the plants.

Estimates of the actual LRP response functions of wheat to N application from equation (4) for each site-year are presented in table II-5. The estimates in the columns under "Response to Preplant Nitrogen" are estimated using the LRP functional form in SAS PROC NLMIXED. The intercept and slope in the last two columns are adjusted for the application of 34 kg ha^{-1} NH_3 pre-plant *and* for the assumed topdress NUE of 0.50. As is noted in table II-5, some of the estimated parameters have no standard errors. This occurs because the data for some site-years do not reach a plateau. In these cases, PROC NLMIXED estimated a linear model, but generated a plateau equal to the expected yield at the maximum rate applied in the data for these site-years. These estimates without standard errors are biased downward, because they tell us only that the plateau is expected to be greater than or equal to the estimate. This is also the case for estimates of the slope given without standard errors. At the Lahoma site in 2007, it appears "likely" that no data points are found on the slope of the production function. Figure II-2 illustrates this type of data limitation. In these instances, the estimate is a lower bound on the expected value of the slope parameter. The dashed lines show how the true production function might deviate from the estimated function, but exactly how likely the slope is to be higher or lower than the parameter estimated in PROC NLMIXED cannot

Table II-4. Unrestricted and Restricted Linear Response-Plateau Functions of Wheat Yield as a Function of Nitrogen Application with Random Parameters for Site-Year

		Estimates	
Parameter	Definition	Unrestricted	Restricted[a]
α	Yield intercept	1862.91***[b]	1974.27***
		(76.68)[c]	(74.78)
β	Nitrogen response	13.28***	18.68***
		(0.97)	(1.45)
P	Yield plateau	3235.93***	3092.16***
		(209.94)	(92.99)
σ_v^2	Variance of site-year intercepts	549216.00***	596678.00***
		(63465.00)	(76819.00)
σ_υ^2	Variance of slope by site-year	89.88***	-
		(11.46)	
σ_ω^2	Variance of plateau by site-year	849818.00***	675736.00***
		(204510.00)	(98987.00)
σ_ε^2	Variance of error	398045.00***	435674.00***
		(17807.00)	(19104.00)
Log Likelihood		-9041.50	-9069.00

[a] In the restricted model the rate of crop response to N is restricted to be constant across time and space—i.e., $\sigma_\upsilon^2 = 0$.
[b] Three asterisks indicate significance at the 0.01 level.
[c] Numbers in parentheses are standard errors

be determined. Note also that for the Perkins 1 site in 2001 there are no standard errors for the intercept or plateau parameters. In this case, PROC NLMIXED estimated the mean yield for the site-year, but failed to provide standard errors because of data constraints. The fact that all points occur on the plateau means that no Monte Carlo simulation is necessary because the mean is linear in parameters. Thus, the lack of standard errors for the plateau and intercept in this site-year is not problematic. Table II-6 contains the estimated predictions of the production function parameters based on the RS

Table II-5. Estimated Wheat Yield Response to Nitrogen by Site-Year (kg ha^{-1})

		Response to Preplant Nitrogen[a]			Response to Topdress Nitrogen[b]	
Location	Year	Intercept	Slope	Plateau	Intercept	Slope
Perkins 1	1998	1134.29***[c]	8.30***	2102.74***	1413.22***	12.58***
		(132.77)[d]	(1.80)	(131.31)	(92.76)	(2.73)
Perkins 2	1998	1317.07***	1.22	1487.45***	1358.81***	1.84
		(94.24)	(1.30)	(107.72)	(70.13)	(1.98)
Tipton	1998	2935.56***	12.65***	5062.48***	3360.64***	19.17***
		(93.45)	(0.43)	(20.38)	(94.57)	(0.66)
Efaw 1	1999	1040.74***	5.46***	3068.47***	1224.28***	8.28***
		(226.18)	(1.50)	(323.25)	(190.75)	(2.27)
Efaw 2	1999	2169.25***	19.27***	3514.70***	2816.67***	29.19***
		(192.74)	(4.22)	(96.28)	(112.42)	(6.39)
Haskell	1999	1768.76***	7.71[e]	2072.38***	1947.74***	11.68[e]
		(288.46)		(182.19)	(226.15)	
Lahoma	1999	1515.33***	26.28***	4443.15***	2398.26***	39.81***
		(116.71)	(2.28)	(181.26)	(76.65)	(3.46)
Perkins 1	1999	1077.36***	12.71**	2431.31***	1504.52***	19.26**
		(177.51)	(4.48)	(125.40)	(127.99)	(6.97)
Stillwater	1999	856.21***	10.90**	1712.31***	1222.49***	16.51**
		(103.45)	(4.00)	(110.48)	(112.42)	(6.06)
Efaw 1	2000	911.47**	26.84***	3384.16***	1813.15***	40.66***
		(380.23)	(6.58)	(294.25)	(251.52)	(9.96)
Efaw 2	2000	2238.16***	-1.44	2157.28***	2290.41***	-2.19
		(579.50)	(6.18)	(415.06)	(510.02)	(9.37)
Haskell	2000	4196.11***	-13.24***	2712.31***	4196.11***	-20.05***
		(342.80)	(1.16)	(212.27)	(342.80)	(1.76)
Hennessey	2000	3834.75***	-0.30	3818.00***	3885.96***	-0.45
		(453.78)	(4.84)	(324.21)	(389.98)	(7.33)
Lahoma	2000	1944.22***	25.02***	3515.79***	2784.92***	37.91***
		(152.57)	(6.09)	(130.53)	(152.61)	(9.23)
Perkins 1	2000	2595.37***	6.72	3349.30***	2914.42***	10.18
		(717.43)	(14.80)	(320.53)	(473.60)	(22.42)
Stillwater	2000	1120.70***	17.05***	3414.03***	1693.60***	25.83***
		(82.93)	(1.34)	(96.49)	(94.26)	(2.02)
Efaw 1	2001	922.02***	15.52**	2024.20***	1444.13***	23.51**
		(215.41)	(6.80)	(112.39)	(169.24)	(10.31)
Efaw 2	2001	2693.64***	8.80	3302.01***	2990.96***	13.33
		(284.51)	(6.22)	(142.12)	(165.32)	(9.43)
Haskell	2001	3671.28**	-6.79	3121.73***	3729.64**	-10.28
		(1365.35)	(10.90)	(385.81)	(1273.98)	(16.51)
Hennessey	2001	1946.76***	7.04***	2815.15***	2183.37***	10.67***
		(185.85)	(0.77)	(91.11)	(187.39)	(1.16)

Table II-5. Estimated Wheat Yield Response to Nitrogen by Site-Year (kg ha^{-1})

		Response to Preplant Nitrogen[a]			Response to Topdress Nitrogen[b]	
Location	Year	Intercept	Slope	Plateau	Intercept	Slope
Lahoma	2001	1478.61***	4.06	1660.92***	1609.78***	6.15
		(201.51)	(17.24)	(142.35)	(161.70)	(26.11)
Perkins 1	2001	2602.04[f]	-1.35	2602.04[f]	2602.04[f]	-2.05
			(1.09)			(1.66)
Stillwater	2001	1054.34***	12.70**	1636.44***	1453.42***	19.24**
		(142.81)	(5.52)	(142.68)	(133.56)	(8.37)
Efaw 1	2002	732.68**	30.94***	2705.97***	1772.32***	46.88***
		(325.21)	(10.27)	(177.95)	(256.69)	(15.56)
Efaw 2	2002	1811.94***	19.94***	3575.16***	2482.00***	30.21***
		(304.84)	(6.67)	(152.27)	(177.87)	(10.10)
Haskell	2002	3501.86***	-13.99*	3112.52***	3504.77***	-21.19*
		(938.58)	(7.45)	(262.09)	(931.44)	(11.29)
Hennessey	2002	4070.50***	-11.74***	3006.29***	4070.50***	-17.79***
		(27.88)	(2.43)	(188.36)	(27.88)	(3.68)
Lahoma	2002	2711.54***	16.54[e]	3076.05***	3055.35***	25.06[e]
		(194.98)		(123.15)	(116.73)	
Perkins 1	2002	2712.02***	1.55***	2972.02***	2754.83***	2.34***
		(192.23)	(0.18)	(161.73)	(182.74)	(0.27)
Stillwater	2002	961.67***	16.03***	2987.29***	1500.18***	24.28***
		(77.42)	(1.55)	(114.73)	(57.42)	(2.34)
Efaw 1	2003	1077.56**	24.02***	3996.74***	1884.67***	36.39***
		(477.36)	(8.25)	(319.92)	(315.96)	(12.51)
Efaw 2	2003	2792.49***	20.30***	4951.01***	3474.71***	30.76***
		(403.15)	(6.03)	(312.27)	(247.42)	(9.14)
Hennessey	2003	2337.38***	14.97***	3760.48***	2840.21***	22.67***
		(256.06)	(3.65)	(166.13)	(155.65)	(5.45)
Lahoma	2003	2761.06***	46.42***	5716.43***	4320.91***	70.34***
		(209.32)	(8.31)	(177.36)	(213.50)	(12.59)
Perkins 1	2003	2796.88***	12.81**	3779.36***	3227.33***	19.41**
		(190.97)	(4.82)	(134.91)	(137.43)	(7.31)
Stillwater	2003	1136.60***	19.87***	2473.35***	1804.27***	30.11***
		(176.81)	(6.86)	(144.20)	(192.42)	(10.40)
Efaw 1	2004	2079.91***	22.88	4132.75***	2876.84***	34.67
		(570.38)	(18.03)	(284.82)	(435.75)	(27.32)
Lahoma	2004	1871.81***	29.23[e]	2526.83***	2494.10***	44.28[e]
		(313.71)		(198.14)	(187.90)	
Lake C.B.	2004	2227.58***	18.20***	4063.87***	2839.27***	27.58***
		(248.15)	(2.14)	(32.35)	(258.30)	(3.24)
Perkins 1	2004	1936.71***	19.76*	3400.00***	2600.53***	29.94*
		(393.43)	(9.94)	(277.93)	(278.81)	(15.06)

Table II-5. Estimated Wheat Yield Response to Nitrogen by Site-Year (kg ha^{-1})

		Response to Preplant Nitrogen[a]			Response to Topdress Nitrogen[b]	
Location	Year	Intercept	Slope	Plateau	Intercept	Slope
Stillwater	2004	2083.09	-2.79	1895.09***	2414.14	-4.23
		(2250.01)	(28.29)	(220.35)	(1839.38)	(42.87)
Efaw 1	2005	1164.61***	4.56***	2845.82***	1317.92***	6.91***
		(210.34)	(1.39)	(299.78)	(176.90)	(2.11)
Lahoma	2005	1754.27***	18.43**	2683.39***	2364.13***	27.93**
		(188.05)	(7.27)	(151.47)	(164.96)	(11.02)
Perkins 1	2005	3494.79***	9.84[e]	4021.72***	3779.16***	14.91[e]
		(267.25)		(177.92)	(221.90)	
Stillwater	2005	1764.54***	15.36[e]	2223.70***	2174.24***	23.27[e]
		(145.73)		(118.83)	(106.79)	
Efaw 1	2006	1081.40***	8.05	2291.85***	1354.89***	12.20
		(275.89)	(4.77)	(174.342)	(185.58)	(7.23)
Lahoma	2006	2230.05***	4.02	2680.96	2370.28***	6.10
		(199.72)	(3.16)		(141.41)	(4.82)
Lake C.B.	2006	1277.70***	37.68***	4377.51***	2543.71***	57.09***
		(291.00)	(8.17)	(290.73)	(216.95)	(12.38)
Perkins 1	2006	917.34***	12.33***	2053.65***	1331.58***	18.68***
		(113.68)	(2.87)	(80.30)	(81.99)	(4.35)
Stillwater	2006	1333.57***	-5.64***	772.78***	1333.57***	-8.54***
		(0.017)	(0.68)	(40.67)	(0.17)	(1.03)
Lahoma	2007	2540.88***	28.81[e]	3163.16***	3157.96***	43.64[e]
		(177.15)		(129.19)	(124.89)	
Lahoma	2008	2761.74***	59.54***	5525.72***	4758.76***	90.21***
		(294.05)	(11.75)	(251.57)	(288.55)	(17.80)
Stillwater	2008	1381.28***	15.99***	2697.67***	1918.22***	24.22***
		(147.22)	(4.32)	(250.85)	(127.64)	(6.54)
Mean for all site-years		2006.22***	13.19***	3073.16***	2473.86***	19.98***
		(125.30)	(1.92)	(140.05)	(125.55)	(2.91)

[a] Parameters and standard errors are estimated using PROC NLMIXED in SAS.
[b] Parameters and standard errors are estimated by Monte Carlo Simulation using PROC IML in SAS.
[c] One, two, or three asterisks (*) indicate statistical significance at the 0.10, 0.05 or 0.01 level, respectively.
[d] Numbers in parentheses are standard errors.
[e] Standard error cannot be estimated due to lack of data points on the slope or plateau. The estimated parameter is biased downward.
[f] Standard errors for the intercept and plateau are not estimated because all available data are on the plateau.

for each site-year. Standard errors for some of these estimates are missing due to the same data limitations described above.

Table II-7 displays the predicted yields at the farmer practice preplant application level of 34 kg ha^{-1} (i.e., the intercept) and the predicted yield from the maximum rate applied in the experiment for each site-year based on the NRS (or the plateau), calculated in equations (14) and (17). In two instances, standard errors for the intercept cannot be estimated because of the same data limitations that disallowed estimation of standard errors for some parameters in tables II-5 and II-6. In two other instances standard errors cannot be estimated for the plateau because the upper bound on the plateau from equation (21) is binding.

Table II-8 displays the nonparametrically bootstrapped means of expected revenues and costs over all site-years for each system. These estimates indicate that, on average, the system expected to be most profitable (aside from the perfect predictors) is the ER system, or the historical extension recommendation of 90 kg N ha^{-1}. The four prediction methods based on ORI data all earn expected returns above N related costs between \$612.90 ha^{-1} (RSD system) and \$623.60 ha^{-1} (RSU system) where N-related costs include N acquisition and application costs and (if needed) the cost of creating a RS or NRS. The ER system, on the other hand, earns an expected return of \$642.45 ha^{-1}. However, based on the results in table II-8, it is inferred that the ER system does not have the advantage of increased yields relative to the RSU and NRSU methods, but instead attains relatively higher profits by using relatively inexpensive NH_3, rather than using UAN.

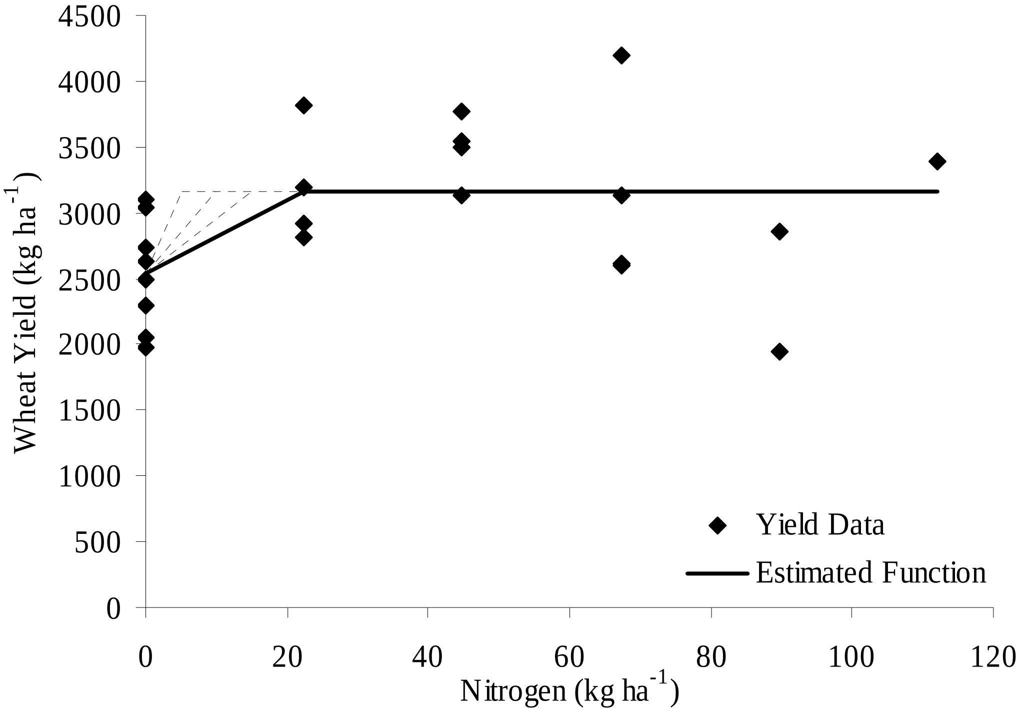

Figure II-2. Plot of yield data and estimated production function for Lahoma 2007.

To test for differences in expected profits, expected yields, and total N application rates between systems, the null hypothesis that the mean paired difference is zero over all site-years is tested. The bootstrapped means of the paired differences between all systems for expected yield, N application rate, and expected profit are presented in table II-9. The mean of the paired-differences in expected profit between the RSU and ER systems is -\$18.85 ha^{-1}, meaning that for any given site-year, the ER system is expected to be more profitable than the RSU system by \$18.85 ha^{-1}. This result is statistically different from zero at the 0.01 significance level. Note also that N application rates for the ER system are always significantly higher than those of any other system by at least 10.23 kg ha^{-1}. Yet, the profits of the ER system are always significantly higher than any

Table II-6. Midseason Predicted Wheat Yield Response to Nitrogen Based on the Ramped Strip Method

		Response to Pre-plant Nitrogen[a]			Response to Topdress Nitrogen[b]	
Location	Year	Intercept	Slope	Plateau	Intercept	Slope
Perkins 1	1998	2780.65[***c]	14.64[***]	4556.02[***]	3272.56[***]	22.18[***]
		(265.23)[d]	(3.59)	(267.92)	(185.21)	(5.44)
Perkins 2	1998	2601.47[***]	7.85	3345.32[***]	2868.37[***]	11.90
		(191.86)	(4.83)	(138.43)	(137.05)	(7.31)
Tipton	1998	3649.34[***]	7.95[***]	4985.08[***]	3916.54[***]	12.05[***]
		(54.79)	(0.13)	(32.82)	(54.98)	(0.20)
Efaw 1	1999	1663.23[***]	12.90[***]	3011.21[***]	2096.78[***]	19.55[***]
		(192.82)	(3.32)	(124.44)	(127.42)	(5.03)
Efaw 2	1999	3636.35[***]	12.74[***]	4469.20[***]	4064.31[***]	19.30[***]
		(201.66)	(4.40)	(102.89)	(117.03)	(6.66)
Haskell	1999	2905.44[***]	4.03[***]	3580.39[***]	3040.79[***]	6.10[***]
		(112.57)	(0.19)	(81.45)	(112.76)	(0.29)
Lahoma	1999	2898.13[***]	18.29[***]	4500.94[***]	3512.83[***]	27.72[***]
		(106.16)	(2.82)	(119.37)	(76.10)	(4.27)
Perkins 1	1999	2015.49[***]	10.42[**]	2741.47[***]	2364.79[***]	15.79[**]
		(185.46)	(4.66)	(133.82)	(131.08)	(7.07)
Stillwater	1999	2499.07[***]	14.52[e]	3149.95[***]	2942.00[***]	21.99[e]
		(211.66)		(174.31)	(177.10)	
Efaw 1	2000	2474.01	215.80[*]	31619.20[***]	9725.74[***]	326.96[**]
		(4252.64)	(73.27)	(3361.26)	(2811.59)	(111.01)
Efaw 2	2000	5378.49[***]	6.77[***]	6209.10[***]	5602.27[***]	10.26[***]
		(257.01)	(0.37)	(215.52)	(251.36)	(0.56)
Haskell	2000	2738.66[***]	3.06[***]	3250.08[***]	2840.89[***]	4.63[***]
		(139.80)	(0.21)	(107.12)	(138.87)	(0.31)
Hennessey	2000	7053.89[***]	2.82[*]	7372.74[***]	7149.16[***]	4.28[*]
		(108.12)	(1.61)	(85.54)	(67.42)	(2.44)
Lahoma	2000	4600.88[***]	70.79[***]	10166.41[***]	6979.50[***]	107.26[***]
		(281.30)	(7.47)	(316.29)	(201.65)	(11.32)
Perkins 1	2000	3559.74[***]	7.51	4658.93[***]	3817.00[***]	11.38
		(500.18)	(6.89)	(559.10)	(365.39)	(10.45)
Stillwater	2000	2801.92[***]	44.20[***]	7020.79[***]	4287.07[***]	66.97[***]
		(262.29)	(5.21)	(396.97)	(194.15)	(7.90)
Efaw 1	2001	2979.90[***]	25.47[***]	5808.81[***]	3835.71[***]	38.59[***]
		(504.87)	(8.70)	(345.58)	(333.77)	(13.18)
Efaw 2	2001	5857.00[***]	8.94[e]	6341.28[***]	6083.65[***]	13.54[e]
		(438.45)		(180.54)	(361.27)	
Haskell	2001	3401.51[***]	4.17[***]	4098.37[***]	3541.15[***]	6.31[***]
		(170.63)	(0.26)	(129.67)	(170.15)	(0.39)
Hennessey	2001	3776.63[***]	18.85[***]	6085.94[***]	4409.69[***]	28.56[***]
		(526.41)	(2.75)	(189.13)	(533.57)	(4.17)

Table II-6. Midseason Predicted Wheat Yield Response to Nitrogen Based on the Ramped Strip Method

		Response to Pre-plant Nitrogen[a]			Response to Topdress Nitrogen[b]	
Location	Year	Intercept	Slope	Plateau	Intercept	Slope
Lahoma	2001	4537.59***	8.30	4902.24***	4794.60***	12.58
		(419.53)	(16.81)	(366.59)	(304.53)	(25.27)
Perkins 1	2001	5147.71***	0.76***	5269.05***	5162.53***	1.14***
		(357.89)	(0.12)	(344.26)	(350.91)	(0.18)
Stillwater	2001	3498.39***	29.31	5298.68***	4458.19***	44.40
		(448.18)	(17.24)	(457.32)	(437.70)	(26.12)
Efaw 1	2002	2494.26***	17.36	3399.27***	3053.07***	26.30
		(590.34)	(18.56)	(301.19)	(375.59)	(28.12)
Efaw 2	2002	3084.92***	16.04***	4010.71***	3623.79***	24.30***
		(120.76)	(2.63)	(61.61)	(70.26)	(3.99)
Haskell	2002	2316.34***	6.44***	3394.45***	2532.71***	9.76***
		(175.97)	(0.56)	(82.64)	(177.01)	(0.85)
Hennessey	2002	4220.91***	-10.41***	3034.33***	4220.91***	-15.77***
		(46.81)	(3.41)	(247.43)	(46.81)	(5.16)
Lahoma	2002	4405.97***	50.74[e]	5543.69***	5470.47***	76.88[e]
		(609.39)		(388.45)	(368.07)	
Perkins 1	2002	3802.37***	3.81***	4441.12***	3930.42***	5.77***
		(109.02)	(0.14)	(87.58)	(109.11)	(0.21)
Stillwater	2002	1885.44***	22.84***	3532.97***	2652.93***	34.61***
		(73.11)	(2.81)	(74.60)	(79.23)	(4.26)
Efaw 1	2003	1440.55***	8.12***	3461.78***	1713.30***	12.30***
		(243.77)	(2.37)	(227.07)	(189.98)	(3.58)
Efaw 2	2003	3089.91***	21.12**	4569.47***	3799.65***	32.00**
		(429.42)	(9.36)	(219.09)	(249.14)	(14.18)
Hennessey	2003	6376.15***	28.20***	9823.25***	7315.84***	42.72***
		(1109.66)	(5.05)	(493.01)	(1106.04)	(7.65)
Lahoma	2003	2633.94***	84.77***	5720.81***	5362.76***	128.43***
		(211.70)	(18.00)	(152.75)	(386.68)	(27.27)
Perkins 1	2003	1964.74***	7.97***	3301.55***	2232.63***	12.08***
		(117.98)	(0.54)	(27.98)	(119.37)	(0.81)
Stillwater	2003	1609.17***	22.71***	3240.08***	2372.03***	34.40***
		(206.13)	(5.08)	(214.35)	(150.72)	(7.70)
Efaw 1	2004	2241.05***	25.63**	4598.48***	3102.42***	38.83**
		(626.89)	(10.80)	(404.56)	(413.97)	(16.36)
Lahoma	2004	3204.68***	59.88[e]	4542.88***	4478.26***	90.72[e]
		(625.31)		(398.89)	(377.76)	
Lake C.B.	2004	1711.71***	13.89***	4047.72[e]	2178.55***	21.05***
		(174.12)	(2.65)		(119.18)	(4.02)
Perkins 1	2004	2051.15***	7.24***	2940.91***	2294.53***	10.98***
		(137.19)	(1.89)	(153.35)	(96.57)	(2.86)

Table II-6. Midseason Predicted Wheat Yield Response to Nitrogen Based on the Ramped Strip Method

		Response to Pre-plant Nitrogen[a]			Response to Topdress Nitrogen[b]	
Location	Year	Intercept	Slope	Plateau	Intercept	Slope
Stillwater	2004	4099.19***	-19.35***	2789.92***	4099.19***	-29.31***
		(381.92)	(1.89)	(259.23)	(381.92)	(2.87)
Efaw 1	2005	2116.86***	16.69***	4300.82***	2677.57***	25.28***
		(278.66)	(4.80)	(179.84)	(184.17)	(7.27)
Lahoma	2005	2465.40***	19.71***	4061.97***	3127.69***	29.86***
		(118.42)	(3.07)	(126.11)	(81.54)	(4.65)
Perkins 1	2005	2012.52***	8.30***	3298.69***	2291.56***	12.58***
		(110.87)	(1.61)	(140.08)	(79.91)	(2.44)
Stillwater	2005	2513.35***	16.61	3379.27***	3034.40***	25.17
		(252.06)	(9.70)	(257.20)	(233.00)	(14.69)
Efaw 1	2006	1292.66***	9.05*	2425.94***	1598.83***	13.71*
		(288.09)	(4.96)	(185.92)	(192.38)	(7.52)
Lahoma	2006	2140.47***	20.01[e]	2588.77***	2570.54***	30.31[e]
		(193.42)		(123.38)	(117.11)	
Lake C.B.	2006	2187.44***	6.69**	2861.93	2412.79***	10.14**
		(194.16)	(2.96)		(133.42)	(4.48)
Perkins 1	2006	1205.94***	7.07***	2073.49***	1443.37***	10.71***
		(103.44)	(1.43)	(115.63)	(72.83)	(2.16)
Stillwater	2006	1459.09***	6.18***	2285.87***	1666.71***	9.36***
		(151.87)	(0.74)	(52.49)	(153.93)	(1.13)
Lahoma	2007	2233.67***	20.11***	2772.22***	2748.78***	30.47***
		(79.02)	(6.08)	(57.01)	(73.09)	(9.21)
Lahoma	2008	2256.17***	43.78***	6382.98***	3727.27***	66.34***
		(184.04)	(3.66)	(306.67)	(123.24)	(5.55)
Stillwater	2008	3791.70***	20.40[e]	4705.53***	4318.23***	30.92[e]
		(583.49)		(480.53)	(469.85)	
Mean		3033.27***	20.98***	4905.13***	3713.75***	31.78***
		(177.58)	(4.05)	(563.13)	(223.27)	(6.82)

[a] Parameters and standard errors are estimated using PROC NLMIXED in SAS.
[b] Parameters and standard errors are estimated by Monte Carlo Simulation using PROC IML in SAS.
[c] One, two, or three asterisks indicate statistical significance at the 0.10, 0.05, or 0.01 level, respectively.
[d] Numbers in parentheses are standard errors.
[e] Standard error cannot be estimated due to lack of data points on the slope or plateau. The estimated parameter is biased downward.

Table II-7. Predicted Production Function Parameters by Site-Year Using Nitrogen-Rich Strip Method

Location	Year	Intercept	Plateau
Perkins 1	1998	3158.61***[a]	4396.29***
		(142.38)[b]	(204.96)
Perkins 2	1998	2789.74***	3245.98***
		(120.84)	(193.33)
Tipton	1998	3920.44***	4723.57***
		(64.29)	(41.54)
Efaw 1	1999	2130.78***	3103.77***
		(140.53)	(285.14)
Efaw 2	1999	4007.73***	4250.35***
		(105.93)	(151.69)
Haskell	1999	3330.12***	3631.90***
		(131.29)	(12.69)
Lahoma	1999	3457.61***	4343.03***
		(85.27)	(36.29)
Perkins 1	1999	2327.63***	2684.95***
		(101.69)	(53.40)
Stillwater	1999	3050.16***	2185.08**
		(213.49)	(611.85)
Efaw 1	2000	7233.88***	6971.97***
		(1168.10)	(235.44)
Efaw 2	2000	5907.51***	6168.73***
		(240.61)	(180.63)
Haskell	2000	2970.80***	3424.40***
		(185.00)	(48.05)
Hennessey	2000	7146.51***	7000.00[c]
		(94.97)	
Lahoma	2000	6972.21***	7000.00[c]
		(336.26)	
Perkins 1	2000	4335.67***	4466.65***
		(351.40)	(603.75)
Stillwater	2000	4662.74***	6169.02***
		(285.55)	(169.71)
Efaw 1	2001	3703.58***	4704.04***
		(241.03)	(186.22)
Efaw 2	2001	6087.57***	6223.40***
		(234.25)	(161.51)
Haskell	2001	3486.51***	4256.58***
		(223.60)	(43.16)
Hennessey	2001	4322.60***	5347.30***
		(372.65)	(622.55)

Table II-7. Predicted Production Function Parameters by Site-Year Using Nitrogen-Rich Strip Method

Location	Year	Intercept	Plateau
Lahoma	2001	4793.77***	4401.71***
		(990.92)	(779.20)
Perkins 1	2001	5091.45[d]	5209.31***
			(622.93)
Stillwater	2001	4344.78***	3867.74***
		(527.81)	(905.34)
Efaw 1	2002	2959.99***	3411.51***
		(538.97)	(400.82)
Efaw 2	2002	3584.36***	3928.78***
		(80.63)	(49.81)
Haskell	2002	2442.06***	3514.90***
		(218.68)	(294.66)
Hennessey	2002	3179.12[d]	2752.40***
			(466.97)
Lahoma	2002	5229.09***	4619.83***
		(421.34)	(811.98)
Perkins 1	2002	3924.09***	4331.71***
		(104.29)	(65.88)
Stillwater	2002	2597.13***	3480.32***
		(95.76)	(82.63)
Efaw 1	2003	1657.90***	3984.21***
		(124.64)	(227.45)
Efaw 2	2003	3594.90***	4572.98***
		(211.22)	(143.29)
Hennessey	2003	6614.33***	6995.83***
		(746.31)	(39.45)
Lahoma	2003	5439.80***	5984.23***
		(168.69)	(92.23)
Perkins 1	2003	2201.01***	3365.56***
		(84.42)	(182.54)
Stillwater	2003	2240.46***	3180.17***
		(107.86)	(428.03)
Efaw 1	2004	2769.48***	3960.31***
		(466.55)	(561.43)
Lahoma	2004	4221.24***	3472.13***
		(599.98)	(692.61)
Lake C.B.	2004	2672.53	3585.14**
		(2062.01)	(1134.89)
Perkins 1	2004	2262.26***	2962.85***
		(59.32)	(270.42)

Table II-7. Predicted Production Function Parameters by Site-Year Using Nitrogen-Rich Strip Method

Location	Year	Intercept	Plateau
Stillwater	2004	6876.53	1493.38
		(9775.84)	(1313.15)
Efaw 1	2005	2607.52***	4424.14***
		(148.06)	(60.88)
Lahoma	2005	3167.18***	4089.44***
		(116.69)	(48.20)
Perkins 1	2005	2240.86***	3316.89***
		(91.27)	(26.05)
Stillwater	2005	2823.04***	4152.00***
		(91.17)	(113.19)
Efaw 1	2006	1561.72***	2014.65***
		(135.37)	(509.69)
Lahoma	2006	2537.69***	2305.14***
		(128.96)	(165.15)
Lake C.B.	2006	2363.95***	2942.79***
		(136.73)	(157.59)
Perkins1	2006	1429.13***	2412.33***
		(65.29)	(269.00)
Stillwater	2006	1607.07***	3266.03***
		(35.32)	(107.41)
Lahoma	2007	2764.37***	2829.27***
		(61.32)	(140.48)
Lahoma	2008	3496.81***	5459.05***
		(128.52)	(70.97)
Stillwater	2008	4181.72***	4044.30***
		(750.20)	(981.71)
Mean		3669.43***	4125.06***
		(209.44)	(183.22)

Note: All parameters and standard errors are estimated using Monte Carlo simulation.
[a] One, two, or three asterisks indicate statistical significance at the 0.10, 0.05, or 0.01 level, respectively.
[b] Numbers in parentheses are standard errors.
[c] The standard error could not be estimated because the upper bound on the plateau from equation (21).
[d] The standard error could not be estimated because the Hessian from equation (12) is not positive definite.

Table II-8. Nonparametrically Bootstrapped Means and Standard Errors of Expected Net Revenue, Expected Yield Revenue, Expected Nitrogen- and Precision-Related Costs, Nitrogen Application Rates and Yields for Each System Assuming All Preplant Nitrogen from Anhydrous Ammonia

	System						
Revenue/Cost	PPU	PPD	RSD	RSU	NRSU	NRSD	ER
Net Revenue	655.72[a]	648.71	612.90	623.60	622.98	613.69	642.45
($ ha^{-1})	(33.28)	(32.88)	(31.72)	(32.94)	(32.91)	(33.37)	(32.73)
Yield Revenue	739.48	727.57	711.24	724.67	721.28	697.97	714.24
($ ha^{-1})	(33.66)[b]	(32.73)	(32.61)	(33.22)	(33.62)	(34.26)	(32.73)
NH_3 Cost	-19.38	-19.38	-19.38	-19.38	-19.38	-19.38	-51.30
($ ha^{-1})							
Mean UAN Cost	-37.11	-31.85	-47.07	-50.34	-46.34	-33.42	0.00
($ ha^{-1})	(4.60)	(4.35)	(4.73)	(5.01)	(4.46)	(4.16)	
NH_3 Application Cost	-20.49	-20.49	-20.49	-20.49	-20.49	-20.49	-20.49
($ ha^{-1})							
Mean UAN Application Cost	-6.78	-7.15	-8.43	-7.89	-8.79	-7.70	0.00
($ ha^{-1})	(0.61)	(0.58)	(0.45)	(0.52)	(0.39)	(0.54)	
Precision System Cost	0.00	0.00	-2.97	-2.97	-3.29	-3.29	0.00
($ ha^{-1})							
Average Yield	3081.16	3031.53	2963.52	3019.45	3005.35	2908.21	2975.98
(kg ha^{-1})	(140.23)	(136.38)	(135.88)	(138.41)	(140.09)	(142.74)	(136.37)
Mean UAN Rate	33.74	28.95	42.79	45.77	42.13	30.38	0.00
(kg ha^{-1})	(4.18)	(3.96)	(4.30)	(4.56)	(4.05)	(3.78)	

Note: All estimates are significantly different from zero at the 0.01 confidence level.
[a] Numbers in parentheses are standard errors.
[b] Numbers without standard errors are constants.

ORI-based predictors by at least \$18.85 ha^{-1}. This result stems from the much lower cost of NH_3 relative to UAN

Additionally, the results indicate that the correct expected profit maximizing N application rate (PPU system recommendation) is significantly greater than that derived from the deterministic method (PPD system) by 4.79 kg ha^{-1}, and that expected profits at the PPU rate are higher by \$7.01 ha^{-1}. Thus, parameter estimation uncertainty has a significant effect on the expected profit maximizing N application rate, as well as on the optimal expected profit. The RSU system (which accounts for uncertainty) also performs significantly better (at the 0.05 confidence level) than the deterministic RSD system by \$10.69 ha^{-1}, without applying significantly more N (see table II-9). Thus, evidence suggests that accounting for estimation uncertainty can improve predictive accuracy in the case of the ramped strip by increasing expected yield by 55.93 kg ha^{-1} (significant at the 0.01 confidence level) without significantly increasing N application rates. Even so, the RSU system falls short of the perfect prediction (PPU) by \$32.12 ha^{-1}, and short of the ER system by \$18.85 ha^{-1}. Also noteworthy is that the NRSU system attains expected yields greater than the NRSD system by an average of 97.13 kg ha^{-1}. However, the increase in expected profits (\$9.29 ha^{-1}) is not quite significant at the 0.10 confidence level because the NRSU system applies 11.75 kg ha^{-1} more UAN than the NRSD system.

The decrease in profit between the PPU system and the ER system is \$13.27 ha^{-1} per year, which is the maximum value of a perfect predictor. Because the ER system is the best method available for expected profit maximization, this value is the amount by which a perfect predictor of economically optimal topdress N application can increase expected profits. In other words, a producer who applies 90 kg N ha^{-1} as preplant NH_3

Table II-9. Nonparametrically Bootstrapped Means and Standard Errors of the Paired Differences Assuming All Preplant Nitrogen from Anhydrous Ammonia

	Variable		
Difference	Expected Profit ($ ha^{-1})	Expected Nitrogen Rate (kg ha^{-1})	Expected Yield (kg ha^{-1})
PPU-PPD	7.01***	4.79***	49.63***
	(1.35)	(1.22)	(10.68)
PPU-RSD	42.81***	-9.05*	117.64***
	(6.72)	(5.29)	(38.36)
PPU-RSU	32.12***	-12.03**	61.71**
	(4.24)	(4.60)	(25.60)
PPU-NRSD	42.03	3.35	172.95***
	(7.14) ***	(4.23)	(41.82)
PPU-NRSU	32.73***	-8.39*	75.82***
	(4.26)	(4.21)	(26.54)
PPU-ER	13.27**	-22.26***	105.18***
	(4.99)	(4.18)	(33.31)
PPD-RSD	35.80***	-13.84***	68.01*
	(6.64)	(5.10)	(36.25)
PPD-RSU	25.11***	-16.82***	12.08
	(4.24)	(4.62)	(24.41)
PPD-NRSD	35.02***	-1.43	123.31***
	(7.02)	(4.28)	(40.46)
PPD-NRSU	25.72***	-13.18***	26.18
	(4.33)	(4.32)	(26.65)
PPD-ER	6.26	-27.05***	55.54
	(5.33)	(3.96)	(33.68)
RSD-RSU	-10.69**	-2.98	-55.93***
	(4.39)	(2.67)	(16.89)
RSD-NRSD	-0.79	12.41***	55.30
	(9.74)	(4.11)	(49.14)
RSD-NRSU	-10.08	0.66	-41.83
	(7.56)	(4.11)	(37.71)
RSD-ER	-29.54***	-13.21***	-12.47
	(7.27)	(4.30)	(38.22)

Table II-9. Nonparametrically Bootstrapped Means and Standard Errors of the Paired Differences Assuming All Preplant Nitrogen from Anhydrous Ammonia

	Variable		
Difference	Expected Profit ($\$$ ha^{-1})	Expected Nitrogen Rate (kg ha^{-1})	Expected Yield (kg ha^{-1})
RSU-NRSD	9.91	15.38***	111.23**
	(7.25)	(4.05)	(41.85)
RSU-NRSU	0.61	3.63	14.10
	(4.96)	(3.66)	(25.64)
RSU-ER	-18.85***	-10.23**	43.46
	(5.81)	(4.56)	(31.06)
NRSD-NRSU	-9.29	-11.75***	-97.13***
	(5.59)	(1.68)	(26.63)
NRSD-ER	-28.76***	-25.62***	-67.77
	(7.97)	(3.78)	(42.43)
NRSU-ER	-19.46***	-13.87***	29.36
	(4.87)	(4.05)	(29.53)

[a] The difference of nitrogen rate is the mean paired-difference of the total nitrogen applications from each system in each site-year.
[b] One, two, or three asterisks indicate statistical significance at the 0.10, 0.05, or 0.01 level, respectively.
[c] Numbers in parentheses are standard errors.

each year in September would be willing to pay no more than $\$13.27$ ha^{-1} per year for the technology needed to use the PPU system described in this paper.

Table II-10 shows the nonparametrically bootstrapped means and standard errors of the revenues and costs for each of the seven systems assuming that all preplant N must come from dry urea, rather than NH_3. Most notably, the ER system appears to be less profitable than the RSU and NRSU systems in this scenario. The ER system no longer has the advantage of using the relatively less expensive NH_3, and is now required to derive all N from dry urea, which is nearly the same price as UAN solution used by the topdress systems. Note that the yield revenues are the same as those in table II-8, because

N application rates have not changed. The cost of preplant N for all systems increases by a factor of 1.74 when urea is used in place of NH_3; however, the high cost of preplant N application is halved by applying dry urea instead of NH_3. Optimal and predicted topdress rates are unaffected by assumptions concerning the source of preplant N. Table II-11 contains the nonparametrically bootstrapped means and standard errors of the paired profit differences between the various prediction systems given all preplant N must be applied as dry urea instead of NH_3. Under this scenario, the paired differences show the ORI-based predictors are all statistically break-even with the ER system. The paired differences show that, while the differences are not statistically significant, the RSU and NRSU systems are on average more profitable than the ER system by \$4.67 ha^{-1} and \$3.19 ha^{-1}, respectively.

The RSU system in this scenario is more profitable than the RSD system by \$10.69 ha^{-1}, again indicating that in the case of the RS technology, accounting for parameter estimation uncertainty improves the value of the predictor. This difference is significant at the 0.05 confidence level. Since the RSU system does not apply significantly more N than the RSD system (see table II-9), the result suggests that accounting for uncertainty improves the accuracy of the predictors. The ORI-based predictors and the ER system all fall short of the optimal profit by at least \$32.12 ha^{-1}— the paired difference between the PPU and RSU systems. Regardless of the availability of NH3, yield losses cause a large share of the profitability losses of all other systems relative to the PPU system, though all systems (except NRSD) apply significantly more total N than the PPU system (see the paired differences in table II-9). The concomitant decrease in expected yields and increase in average N application rates indicates all these

Table II-10. Nonparametrically Bootstrapped Means and Standard Errors of Expected Net Revenue, Expected Yield Revenue, Expected Nitrogen- and Precision-Related Costs, Nitrogen Application Rates and Yields for Each System Assuming All Preplant Nitrogen from Dry Urea

Revenue/Cost	PPU	PPD	RSD	RSU	NRSU	NRSD	ER
Net Revenue	652.74	645.73	609.92	620.62	619.13	609.84	615.95
(\$ ha^{-1})	(33.28)[a]	(32.88)	(31.72)	(32.94)	(32.91)	(33.37)	(32.73)
Yield Revenue	739.48	727.57	711.24	724.67	721.28	697.97	714.24
(\$ ha^{-1})	(33.66)	(32.73)	(32.61)	(33.22)	(33.62)	(34.26)	(32.73)
Urea Cost	-33.66[b]	-33.66	-33.66	-33.66	-33.66	-33.66	-89.10
(\$ ha^{-1})							
Mean UAN Cost	-37.11	-31.85	-47.07	-50.34	-46.34	-33.42	0.00
(\$ ha^{-1})	(4.60)	(4.35)	(4.73)	(5.01)	(4.46)	(4.16)	
Urea Application Cost	-9.19	-9.19	-9.19	-9.19	-9.19	-9.19	-9.19
(\$ ha^{-1})							
Mean UAN Application Cost	-6.78	-7.15	-8.43	-7.89	-8.79	-7.70	0.00
(\$ ha^{-1})	(0.61)	(0.58)	(0.45)	(0.52)	(0.39)	(0.54)	
Precision System Cost	0.00	0.00	-2.97	-2.97	-4.16	-4.16	0.00
(\$ ha^{-1})							
AverageYield	3081.16	3031.53	2963.52	3019.45	3005.35	2908.21	2975.98
(kg ha^{-1})	(140.23)	(136.38)	(135.88)	(138.41)	(140.09)	(142.74)	(136.37)
Mean UAN Rate	33.74	28.95	42.79	45.77	42.13	30.38	0.00
(kg ha^{-1})	(4.18)	(3.96)	(4.30)	(4.56)	(4.05)	(3.78)	

Note: All estimates are significantly different from zero at the 0.01 confidence level.
[a] Numbers in parentheses are standard errors.
[b] Numbers without standard errors are constants.

Table II-11. Nonparametrically Bootstrapped Means and Standard Errors of Paired Differences in Profits Given All Preplant Nitrogen from Dry Urea

Difference	Expected Profit ($\$$ ha^{-1})
PPU-PPD	7.01***
	(1.35)
PPU-RSD	42.81***
	(6.72)
PPU-RSU	32.12***
	(4.24)
PPU-NRSD	42.90***
	(7.14)
PPU-NRSU	33.60***
	(4.26)
PPU-ER	36.79***
	(4.99)
PPD-RSD	35.80***
	(6.64)
PPD-RSU	25.11***
	(4.24)
PPD-NRSD	35.89***
	(7.02)
PPD-NRSU	26.59***
	(4.33)
PPD-ER	29.78***
	(5.33)
RSD-RSU	-10.69**
	(4.39)
RSD-NRSD	0.08
	(9.74)
RSD-NRSU	-9.21
	(7.56)
RSD-ER	-6.02
	(7.27)
RSU-NRSD	10.78
	(7.25)

Table II-11. Nonparametrically Bootstrapped Means and Standard Errors of Paired Differences in Profits Given All Preplant Nitrogen from Dry Urea

Difference	Expected Profit ($\$ ha^{-1}$)
RSU-NRSU	1.48
	(4.96)
RSU-ER	4.67
	(5.81)
NRSD-NRSU	-9.29
	(5.59)
NRSD-ER	-6.11
	(7.97)
NRSU-ER	3.19
	(4.87)

Note: Only paired-differences in expected profits are shown. Paired differences for the other variables are the same as in table II-9.
[a] One, two, or three asterisks indicate statistical significance at the 0.10, 0.05, or 0.01 level, respectively.
[b] Numbers in parentheses are standard errors.

systems have a tendency to over-apply when N is not needed and under-apply when it is needed.

Table II-12 contains the nonparametrically bootstrapped means of expected revenues and costs for each of the seven systems assuming that topdress N midseason is no more efficient than preplant N application—i.e., NUE for both preplant and topdress applications is 33%. These results show that without the assumption of a large improvement in NUE for topdress N as opposed to preplant N, the ER system is more profitable than even the PPU system on average ($\$642.45\ ha^{-1}$ vs. $\$637.72\ ha^{-1}$). This is partially because the ER system reduces average N purchase costs relative to the PPU system by $\$11.65\ ha^{-1}$ by using only NH_3 instead of using a split N application of preplant NH_3 and topdress UAN. The ER system also avoids the cost of custom UAN application, thus saving another $\$6.05\ ha^{-1}$ relative to the PPU system. However, expected revenue from grain sales for the PPU system is higher than that of the ER system by \$12.97 ha^{-1}, largely offsetting the cost savings on N purchase and application costs.

Table II-13 displays the mean paired differences of expected profits, total N application rates, and yields between the seven systems, revealing that the profitability difference of \$4.72 ha^{-1} per year between the PPU and ER systems is not statistically significant, though the ER system *is* statistically more profitable than the PPD system by \$11.04 ha^{-1} at the 0.05 confidence level. Ultimately, these results show that if crop response to topdress UAN is the same as crop response to preplant NH_3, the ER system is more profitable than any of the ORI-based predictors by at least \$35.53 ha^{-1}—the paired difference between the PPU and RSU systems. Additionally of interest is the finding that the RSU system is more profitable than its deterministic counterpart by an average of \$10.22 ha^{-1}, without applying significantly more N on average, showing yet again that accounting for parameter uncertainty improves the accuracy of RS-based predictions of the economically optimal N application rate. However, even with this improved prediction accuracy, the ER system is still significantly more profitable than the RSU system by \$35.53 ha^{-1} ($p = 0.01$).

Conclusions

The findings of this research indicate that applying 90 kg N ha^{-1}, which is the historical extension advice for Oklahoma, is the method with the highest expected profit. However, this result is sensitive to the assumption N is applied as NH_3 prior to planting. Because

Table II-12. Nonparametrically Bootstrapped Means and Standard Errors of Expected Net Revenue, Expected Yield Revenue, Expected Nitrogen- and Precision-Related Costs, Nitrogen Application Rates and Yields for Each System Assuming No Increase in Nitrogen-Use Efficiency

	System						
Revenue/Cost	PPU	PPD	RSD	RSU	NRSU	NRSD	ER
Net Revenue	637.72	631.41	596.70	606.92	600.35	597.90	642.45
($ ha^{-1})	(33.29)[a]	(33.17)	(32.23)	(32.60)	(33.24)	(33.45)	(32.73)
Yield Revenue	727.21	724.24	709.20	714.11	712.26	699.90	714.24
($ ha^{-1})	(34.38)	(32.93)	(32.35)	(32.95)	(34.07)	(34.38)	(32.73)
NH_3 Cost	-19.38[b]	-19.38	-19.38	-19.38	-19.38	-19.38	-51.30
($ ha^{-1})							
Mean UAN Cost	-43.57	-45.45	-61.22	-57.20	-60.31	-51.14	0.00
($ ha^{-1})	(5.69)	(5.57)	(6.41)	(6.45)	(6.07)	(5.93)	
NH_3 Application Cost	-20.49	-20.49	-20.49	-20.49	-20.49	-20.49	-20.49
($ ha^{-1})							
Mean UAN Application Cost	-6.05	-7.51	-8.43	-7.15	-8.43	-7.70	0.00
($ ha^{-1})	(0.65)	(0.55)	(0.45)	(0.59)	(0.45)	(0.54)	
Precision System Cost	0.00	0.00	-2.97	-2.97	-3.29	-3.29	0.00
($ ha^{-1})							
Average Yield	3030.04	3017.67	2954.98	2975.47	2967.74	2916.25	2975.98
(kg ha^{-1})	(143.26)	(137.22)	(134.79)	(137.27)	(141.95)	(143.27)	(136.37)
Mean UAN Rate	39.61	41.32	55.66	52.00	54.83	46.49	0.00
(kg ha^{-1})	(5.17)	(5.06)	(5.83)	(5.86)	(5.52)	(5.39)	

Note: All estimates are significantly different from zero at the 0.01 confidence level.
[a] Numbers in parentheses are standard errors.
[b] Numbers without standard errors are constants.

Table II-13. Nonparametrically Bootstrapped Means and Standard Errors of the Paired -Differences Assuming No Nitrogen-Use Efficiency Increase from Midseason Application

Difference	Expected Profit ($ ha^{-1})	Expected Nitrogen Rate[a] (kg ha^{-1})	Expected Yield (kg ha^{-1})
PPU-PPD	6.32***	-1.72	12.37
	(1.20)	(3.19)	(16.09)
PPU-RSD	41.02***	-16.05**	75.05*
	(6.62)	(6.40)	(38.24)
PPU-RSU	30.80***	-12.39**	54.56*
	(4.59)	(5.43)	(29.09)
PPU-NRSD	39.82***	-6.88	113.79***
	(6.53)	(6.12)	(41.81)
PPU-NRSU	37.37***	-15.22**	62.30*
	(5.46)	(5.92)	(33.52)
PPU-ER	-4.72	-16.39***	54.05*
	(4.56)	(5.17)	(30.28)
PPD-RSD	34.70***	-14.34**	62.68*
	(6.68)	(5.99)	(33.93)
PPD-RSU	24.49***	-10.68**	42.19*
	(4.81)	(5.21)	(24.66)
PPD-NRSD	33.51***	-5.17	101.42**
	(6.69)	(5.86)	(38.07)
PPD-NRSU	31.05***	-13.51**	49.93
	(5.67)	(5.76)	(30.03)
PPD-ER	-11.04**	-14.68***	41.68
	(4.88)	(5.06)	(29.58)
RSD-RSU	-10.22**	3.66	-20.49
	(3.85)	(3.73)	(14.98)
RSD-NRSD	-1.20	9.17*	38.74
	(8.81)	(5.35)	(48.66)
RSD-NRSU	-3.65	0.83	-12.75
	(7.91)	(5.15)	(42.79)
RSD-ER	-45.74***	-0.34	-21.00
	(7.29)	(5.83)	(36.46)

Table II-13. Nonparametrically Bootstrapped Means and Standard Errors of the Paired -Differences Assuming No Nitrogen-Use Efficiency Increase from Midseason Application

Difference	Expected Profit ($ ha^{-1})	Expected Nitrogen Rate[a] (kg ha^{-1})	Expected Yield (kg ha^{-1})
RSU-NRSD	9.02	5.51	59.23
	(6.92)	(4.97)	(42.59)
RSU-NRSU	6.57	-2.83	7.74
	(5.93)	(4.61)	(34.93)
RSU-ER	-35.53***	-4.00	-0.51
	(6.16)	(5.86)	(31.18)
NRSD-NRSU	-2.45	-8.34***	-51.49
	(2.56)	(1.33)	(13.56)
NRSD-ER	-44.55***	-9.51*	-59.74
	(7.71)	(5.39)	(42.17)
NRSU-ER	-42.09***	-1.17	-8.25
	(6.38)	(5.52)	(35.07)

[a] The difference of nitrogen rate is the mean paired-difference of the total nitrogen applications from each system in each site-year.
[b] Numbers in parentheses are standard errors.
[c] One, two, or three asterisks indicate statistical significance at the 0.10, 0.05, or 0.01 level, respectively.

NH_3 is much less expensive than urea or UAN, the historical extension recommendation entails significantly less expenditure on N than any of the ORI-based systems in this analysis. Additionally, the ORI-based systems require a split application, which means that producers must pay for preplant application of NH_3, as well as midseason topdress application of UAN.

Evidence also indicates that estimation uncertainty does have a significant effect on expected profit maximization using linear response-plateau functions, in that the true expected profit maximizing N application rate averages 4.73 kg ha^{-1} higher than the rate found using the deterministic approach. However, accounting for parameter estimation uncertainty in the ORI-based prediction methods produces mixed results. While accounting for parameter uncertainty significantly improves the profitability of the RS technology, the improvement for the NRS technology is small and not statistically significant. Notably, inclusion of estimation uncertainty in the prediction process does not result in greater expected profits than those achieved by the historical extension recommendation. Importantly, this result indicates that the bulk of prediction error is not a result of estimation uncertainty, but perhaps results from uncertainty about the relationship between the optical reflectance measures and the true parameters of the yield response functions.

Based on equation (3), the estimated marginal product of preplant N in table II-4 is 13.28 kg wheat for each additional kg of N. This estimate translates to 32% NUE on average, assuming no over-application. Another estimate of crop response to preplant N in table II-5, which provides estimates of the production function parameters for each site-year. The estimated marginal product is 13.19 kg wheat per additional kg of N—the mean of the response function slopes for all site-years. This estimate also corresponds to about 32% NUE, which is similar to the 33% found by Raun and Johnson (1999).

One limitation of this study is that it assumes NUE is 33% for preplant N applications, and 50% for midseason topdress applications. Yet, these assumptions are not accurate in all cases, as one of the key findings in this paper is that the marginal product of preplant N varies significantly by site-year (see table II-4 and associated hypothesis test). Based on the parameters of the estimated response functions to preplant N in table II-5, crop response to topdress N must be simulated for each site-year using the above assumptions about NUE. The mean of these simulated crop response rates is 19.98

kg wheat per additional kg of N, which corresponds to about 48% NUE, which is close to 50%. The assumption of 50% NUE implies that average crop response to midseason topdress N application is one and a half times the crop response to preplant N. The accuracy of this assumption is crucial to the ability of the NFOA to accurately predict profit maximizing N application rates. If the marginal product of topdress UAN varies significantly by site-year, for example, this variability should be quantified and integrated into the NFOA and RS technologies

The expected profit maximizing strategy for winter wheat producers in Oklahoma is to apply 90 kg N ha^{-1} as preplant NH_3. This result stems primarily from the relatively low cost of NH_3. However, when NH_3 is not available, the optical reflectance-based predictors are statistically break-even with the historical extension rate in terms of profit, while applying significantly less total N. The reduced N application rates would result in reduced environmental impacts on surface and ground water quality.

A few changes might reduce costs associated with the optical reflectance-based prediction systems. For example, preplant application rate of 34 kg N ha^{-1} as NH_3 assumed in this paper may not be optimal. By increasing this rate a producer could decrease the need for topdress UAN, which could decrease the total costs because NH_3 is cheap relative to UAN, and because some midseason UAN application costs would be eliminated. Also, topdress application costs could be avoided by combining UAN and herbicide applications. However, this prospect seems untenable because weeds need to be sprayed in December, while optical reflectance-based N requirement predictions are not made until February. Additionally, many producers already make split applications without using optical reflectance-based predictions, often applying substantial N as preplant NH_3, and applying more N as UAN later in the season if the crop is doing well. The optical reflectance-based predictors may be profitable for producers who already use split applications with some amount of preplant N from NH_3, urea, or ammonium nitrate. In other words, some producers already prefer split N application systems, likely because they have found split applications to be profitable—that is, the historical extension advice to apply 90 kg N ha^{-1} prior to planting may not be the appropriate benchmark. Another issue relating to benchmarks is that many winter wheat producers in Oklahoma produce dual purpose wheat for both grazing and grain. Many of these producers use split N applications, using preplant N for forage production and midseason topdress UAN application for grain production. However, the optical reflectance-based prediction methods require that wheat forage be present when experimental strips are measured, and therefore would require that producers incur further costs to exclude cattle from the RS or NRS.

Future efforts to improve optical reflectance-based N requirements prediction methods should focus on quantifying and incorporating uncertainty in the nitrogen-rich strip and ramped strip technologies. Sources of uncertainty include uncertainty about the relationship between optical reflectance data and the true parameters of the production functions, as well as uncertainty about post-optical sensing weather. Post-sensing weather may be especially important in dry land winter wheat production. Also particularly beneficial to Oklahoma producers would be adaptations of the optical sensing methods that are easily compatible with the production of dual purpose winter wheat.

CHAPTER III

PREFERENCES FOR ENVIRONMENTAL QUALITY

UNDER UNCERTAINTY

The following chapter has been published in the journal *Ecological Economics* and appears in this dissertation with the journal's permission.

Abstract

Although the expected effects of environmental policies and interventions are rarely known with certainty, stated preference surveys rarely elicit preferences over uncertain environmental outcomes. This article presents empirical results challenging the view that ignoring such uncertainty during preference elicitation is of no consequence so long as people only care about final environmental states. The evidence presented indicates measured preferences for final environmental states—water quality in this case—depend on whether people choose between final states or between lotteries over final states. In contrast to the typical finding for monetary lotteries, this paper shows significant under-weighting of low probability events related to water quality.

Introduction

Stated preference methods such as contingent valuation and conjoint analysis are widely used by environmental economists to carry out cost benefit analysis, analyze the welfare effects of environmental degradation or improvement, and prioritize resource allocation.

The National Oceanic and Atmospheric Administration Panel has recommended (though other formats can be used) that contingent valuation survey instruments ask study participants whether they would vote in favor of a referendum that, if passed, would raise taxes by a given amount and (typically with 100% certainty) would improve a public good by a certain increment (Arrow et al., 1993). Similarly, in conjoint analysis, people are asked to choose, rate, or rank competing scenarios or goods, environmental or otherwise, that differ in terms of the levels of several attributes, where there is usually no explicit uncertainty about the level of an attribute within a scenario (See Green et al., 1972). Unfortunately, real-world decisions, especially where environmental processes are concerned, are rarely as simple.

Even after extensive study and modeling, there is almost always some degree of uncertainty about the effects of environmental policies and interventions. For example, uncertainty persists, despite extensive research and modeling, about the link between global warming and hurricane intensity (and acute heat waves, etc.), as well as whether greenhouse gas reduction policies can reverse or slow the global warming trend (and by association, reduce various climatic perils) at this late date (Curry et al., 2006; Lovelock, 2006). These uncertainties arise because models, as abstractions of reality, do not perfectly capture the characteristics of the biophysical and economic systems they are designed to mimic. This is especially true in the case of systems where environmental outcomes or states of environmental quality depend heavily on stochastic events, such as rain fall, run-off, light conditions, changing land use patterns, etc.

What is the consequence of ignoring this underlying uncertainty when conducting stated preference surveys? One answer is that such uncertainty is of no consequence for the practice of stated preference analysis. In standard economic models, people's utilities are often assumed to depend only on the final states of the environment, health, and/or wealth. Under such an assumption, economists can adjust welfare measures for uncertainty in the effect of a policy on the environment after a survey.

Another view is that the underlying uncertainty might alter preferences for an environmental amenity. Such a situation might arise for several reasons. First, several studies show that people's decisions are influenced by a “certainty-effect” whereby people overweight outcomes that are considered certain relative to outcomes that are probable (Kahneman and Tversky, 1979). This effect is typically captured by arguing that people distort probabilities using non-linear weighting rules as in Kahneman and Tversky's (1979) prospect theory or Quiggin's (1982) rank-dependent expected utility theory. That is, people transform the probability of an event into a decision weight. The typical argument is that people over-weight low probability events and under-weight medium to high probability events (Tversky and Fox, 1995; Prelec, 2000). If people do not weight probabilities linearly, then the utility of a policy option cannot be determined simply by multiplying the utility of end-states by the probabilities of achieving the end-state; instead, one must multiply the utility of end-states by the decision weights associated with the end-states. To confound this issue, these decision weights might be good- and context-specific. Furthermore, Bleichrodt et al. (2001) show that risk preference elicitation approaches that do not control for nonlinear probability weighting often provide biased estimates of people's utility function parameters.

Another factor that might cause people to view an environmental amenity differently in the presence of uncertainty is background risk. Background risk refers to a non-insurable, exogenous risk that will not be resolved until after a particular decision is made. Several papers have investigated the effect of independent, additive background risks on risk taking behavior. Gollier and Pratt (1996) and Eeckhoudt et al. (1996) investigated the conditions under which the addition of, or increase in, background risk causes a utility maximizing individual to make more conservative choices in risky situations. Other authors, such as Diamond (1984) and Quiggin (2003), argue that addition of independent background risks might increase risk taking behavior. While there is no universal agreement on the direction of the anticipated effect of background risk on risk aversion, it is clear that most expect it to indeed have some effect. In a stated preference survey, the endogenous variable is the person's choice, rating, or ranking over alternative environmental/wealth/health outcomes. Introducing uncertainty over outcomes effectively adds an exogenous background risk that cannot be resolved at the time of the rating, ranking, or choice. As argued by Eeckhoudt et al. (1996) in general, and by Eeckhoudt and Hammitt (2001) in the context of the value of statistical life, addition of this background risk might be expected to alter preferences for environmental outcomes.

Since the studies of McFadden (1973) and Haneman (1984), random utility theory has become the dominant paradigm for modeling individual choice when carrying out environmental valuation. However, there are surprisingly few applications of random utility models dealing with environmental issues in which natural uncertainty is included in the underlying outcomes. Starmer (2000) reviewed several approaches for introducing a stochastic process into the theories of individual decision making under risk, but as he makes clear, there is no consensus on the most appropriate approach. Strictly speaking, expected utility theory and other such theories of individual behavior under risk are deterministic theories. This suggests a potential synthesis of the models of individual decision making under risk and random utility theory, which results in a random expected utility model.

A few previous empirical studies have considered uncertainty in environmental outcomes (e.g., Edwards, 1988; Cameron, 2005). Cameron (2005) elicited subjective probabilities from undergraduate economics students to determine the effects of the subjects' prior knowledge and expectations for climate change on their willingness-to-pay (WTP) to avoid climate change. Edwards (1988) focused more on uncertainty with regard to policy outcomes; however, both Cameron (2005) and Edwards (1988) estimated option value—or the value that respondents place on the option to use particular resources in the future—given the underlying uncertainty. McConnell et al. (1995) estimated a random utility model where there was uncertainty in the expected catch that an angler could expect to observe. A few other studies have investigated preferences under uncertainty in the context of rationing public goods via lotteries (e.g., Boxall, 1995; Scrogin and Berrens, 2003). None of this prior research attempted to introduce uncertainty in the context of stated preference methods, where probabilistic outcomes must be explicitly introduced into the survey design. Furthermore, previous research has not investigated the effect of uncertainty on elicited preferences, which is an important issue given that the vast majority of contingent valuation and conjoint studies are conducted by asking people to make choices over final environmental outcomes. Finally, previous studies have not considered the consequences of non-linear probability weighting on valuation estimates.

This article determines whether explicitly including uncertainty in the environmental outcomes influences estimates of people's preferences for water quality in a stated preference survey. In particular, a split sample design is used where one group of respondents was presented with a choice-based conjoint question where they were asked to choose one of two lake states of nature they most preferred, where each description of the lake differed by several quality attributes. The other group of respondents received a similar choice-based conjoint question, except the quality attributes in each of three lake alternatives were only known with some probability. The two null hypotheses explicitly tested in this research are 1) that presence of probabilistic outcomes does not affect people's WTP to move, with certainty, from one quality level to another, and 2) that respondents linearly weight the probabilities of obtaining the various end states of nature. In fact, valuation estimates implied by the two survey formats are substantially different; additionally, significant non-linear weighting of probabilities—especially underweighting of low probability events—is detected.

Background

To investigate these issues, recreationists' preferences were elicited for two different environmental conditions at Tenkiller Ferry Reservoir—a man-made lake near Tulsa, Oklahoma—historically known for its crystal-clear waters. The lake and the tail waters of the dam are popular destinations for recreational anglers, as well as participants in myriad types of aquatic recreation, including scuba diving. This application was particularly well suited for analysis for several reasons. There is currently a controversy (and lawsuit) between the states of Oklahoma and Arkansas related to nutrient run-off from excess land application of poultry litter up-stream of the lake in the Lower Illinois River watershed. Due to resulting high nutrient concentrations in the water column, blooms of blue-green algae (cyanobacteria) have become frequent in the lake. In fact, Peridiniopsis polonicum, a species of blue-green alga which could cause toxic fish kills in trout downstream, was found in Tenkiller Lake in 1986 (Nolen et al., 1989; Roset et al., 2002).

However, predicting specific algal bloom events is particularly difficult and the likelihood of an algal bloom occurring depends heavily on other stochastic events, such as rain fall, run-off, and light conditions (Soranno, 1997). Lathrop et al. (1998) were, however, able to determine the average probability of an algal bloom on any given summer day for lake Mendota in Wisconsin based on historical phosphorus concentration data for the lake. They also calculated, based on the data and hydrologic models, the phosphorus load reductions required for various levels of control on the probability of a bloom. Thus, it appears that prediction related to the average water quality is about the best available when it comes to such highly stochastic events, even when vast amounts of data are available. The difficulty is that the effectiveness of any intervention aimed at reducing the chance of an algal bloom is uncertain. For example, policies could be enacted to reduce or eliminate the use of poultry litter as an agricultural fertilizer, which would reduce phosphorus concentrations in resulting run-off. However, because a) litter use is stochastically related to nutrient concentrations in run-off and b) nutrient concentrations in run-off are stochastically related to algal blooms in downstream lakes, the ultimate effect of any policy or intervention is stochastic. In terms of water levels in the lake, intervention strategies might include development of dams or reservoirs that affect the water level at Tenkiller; however, because factors such as rainfall are stochastic, lake water levels are inherently stochastic.

The random utility model of McFadden (1973) is used to address these issues, such that the overall utility of a choice alternative is assumed to depend systematically on the attributes of the alternative, while factors unobservable to the econometrician are accounted for in a stochastic error term. People are assumed to choose the alternative yielding the highest level of utility. Typically, the attributes included in the systematic portion of the utility function are assumed to be known with certainty; however, in this application, the situation is also considered in which a choice alternative has only a probability of possessing some attribute. This approach is entirely consistent with random utility theory, recognizing that the probability with which an outcome results from a choice alternative is simply another attribute of the choice.

To clarify the issues at hand, assume lake attribute levels are known with certainty, and let individual *i*'s random utility from visiting lake *j* be written as:

(1) $$V_{ij} = \alpha_j + \beta(\text{Bloom}) + \gamma(\text{Level}) + \lambda(\text{Cost}) + \varepsilon_{ij},$$

where Bloom is a dichotomous variable that takes the value of 1 if an algal bloom is on the lake, Level refers to the lake water level, Cost is individual *i*'s cost to visit the lake, β is the level of disutility received if a bloom occurs (note: the utility of no bloom is normalized to zero), γ is the marginal utility of water level, λ is the marginal utility of income, α_j is a fixed level of utility associated with all other attributes of lake *j*, and ε_{ij} is a stochastic error term.

Assuming the utility parameters in equation (1), preferences for lake attributes could be measured by some stated preference method where respondents chose, rated, or ranked lakes that differed in terms of whether a bloom was present, a given water level, and cost. Given these data and the assumption that person *i* will visit lake *j* for sure, WTP to remove an algal bloom from the lake could simply be calculated as $-\beta/\lambda$. However, as previously stated, virtually any intervention aimed at reducing algal blooms could not, under any reasonable cost, eliminate all algal blooms. Thus, an analyst might instead be interested in calculating willingness-to-pay to reduce the chance of an algal bloom on any given day from say 30% to 20%, in which case the per-person, per-visit benefit of the policy might be calculated as $(0.3–0.2)(-\beta/\lambda)$. This figure is derived by assuming people utilize expected utility theory to evaluate outcomes where the utility of an outcome is simply multiplied by the probability of that outcome. For example, if the chance of an algal bloom is P_B, then utility of an option *j* is:

(2) $$V_{ij} = \alpha_j + P_B\beta(\text{Bloom}) + \gamma(\text{Level}) + \lambda(\text{Cost}) + \varepsilon_{ij}.$$

However, as alluded to previously, explicitly including uncertainty in the decision making task might influence the valuation measure.[6] Suppose a person were asked to evaluate lake *j* with a P_B chance of a bloom and a P_L chance of lake water Level_1 and $(1-P_L)$ chance of water Level_2. Assuming individual *i* uses decision weights as prospect theory asserts, individual *i*'s random utility from visiting lake *j* can be written as:

(3) $$\begin{aligned} V_{ij} = \alpha_j^{UC} &+ \pi(P_B)\beta^{UC}(\text{Bloom}) + \pi(P_L)\gamma^{UC}(\text{Level}_1) \\ &+ [1-\pi(P_L)]\gamma^{UC}(\text{Level}_2) + \lambda^{UC}(\text{Cost}) + \varepsilon_{ij}. \end{aligned}$$

[6] It is often useful to draw a distinction between the concepts of "uncertainty" and "risk," where the former refers to the case of unquantifiable indeterminacy of potential outcomes, while "risk" refers to the situation in which probabilities of achieving different outcomes are known. Under this distinction, it would be more precise to say that risk, rather than uncertainty, has been included in the decision making task. For expositional convenience, the term uncertainty is used in the text, but it should be clear in this context that probabilities can be assigned to events.

where π is a probability weighting function and the superscript UC refers to marginal utilities when measured over uncertain outcomes (again note that the utility of a non-bloom is normalized to zero). Now, consider a person's WTP to reduce the chance of an algal bloom on any given day from 30% to 20%, which is given by the expression $(\pi(0.3)-\pi(0.2))(-\beta^{UC}/\lambda^{UC})$. Comparing this term to the WTP derived under the case of certainty, it is clear that valuation measures might diverge in one of two ways: either because the probability weighting function is non-linear in probabilities (i.e., $[\pi(0.3)-\pi(0.2)]\neq[0.3-0.2]$) or because people's preferences change when they are aware of the background risk (e.g., $\beta^{UC}\neq\beta$ or $\lambda^{UC}\neq\lambda$).

Methods

To examine these issues, two survey instruments were designed: one that asked respondents to state their preferences for certain outcomes and one that incorporated uncertainty about the outcomes. Respondents randomly received one of the two instruments. Regardless of the treatment to which an individual was assigned, they were asked to choose which lake they most preferred to visit, where each lake option differed by three attributes: algal bloom status, the water level, and a user fee that would be added to either camping or day use fees. The three attributes were varied as follows:

> Algal bloom status: Varied at two levels: Yes or No corresponding to the presence or absence or an algal bloom, respectively.
>
> Water level: Varied at five levels: normal, 2 ft below normal, 5 ft below normal, 8 ft below normal, and 10 ft below normal.
>
> User fee: Varied at five levels: \$0, \$2, \$4, \$6, and \$8.

In the treatment with no uncertainty, a full factorial design was created that combined all levels of every attribute with levels of every other attribute. This produced 5×5×2=50 possible lake descriptions. On each survey, people were asked to answer four binary choice questions, where they chose whether they preferred lake option A or lake option B. For each survey, 8 of the 50 lake descriptions from the full factorial were randomly chosen to construct the survey (4 discrete choice questions×2 options each=8 lake descriptions). Lusk and Norwood (2005) showed that this random assignment of profiles from the full factorial both within and across choices and surveys performed well in terms of efficiency of resulting WTP estimates. Figure III-1 shows an example of one of the choice questions with certainty.

For the choice tasks with uncertainty, two additional attributes were intorduced: the probability of an algal bloom (varied at 100%, 90%, 50%, 10% and 0%) and the probability of water level being either normal, 2 ft low, 5 ft low, 8 ft low, or 10 ft low (varied at 100%, 90%, 50%, 10% and 0%). This means there were essentially four attributes, each varied at five levels, making a full factorial design of 625 possible combinations. Because the full factorial was rather large in this case, it was possible that a random assignment of profiles to choice tasks might produce less than desired results. Thus, a sub-set of profiles was selected from the full factorial to minimize the D-efficiency criterion (Lusk and Norwood, 2005). In particular, 17 unique combinations were selected from the full factorial, which generated a D-efficiency score of 81.53.

For a typical trip to Tenkiller Lake, which of the following options would you prefer? (Please check only the box below your preferred option.)

Attribute	**Option A**	**Option B**
Algae Bloom Status	Bloom	No Bloom
Water Level	2 feet below normal level	Normal level
User fee	$6 user fee	$2 user fee
I would choose . . .	☐	☐

Figure III-1. Choice card from survey without uncertainty.

Rather than specifying a probability for all five water levels and to simplify the decision task, resulting experimental design was used to assign a probability to a particular water level and then the remaining probability (i.e., one minus the probability) was assigned to the normal water level. In cases where both levels happened to be normal, one of the other four water levels was randomly chosen. As in the certainty case, each person was asked to answer four discrete choice questions. To construct the four questions, 8 of the 17 selected lake descriptions were randomly assigned to option A or B to create each survey. Five persons otherwise unrelated to this study who held degrees ranging from high school diploma to doctor of philosophy were consulted independently multiple times to improve the ease of understanding of the survey instrument before the authors settled on the final versions of the surveys as implemented.

In addition to options A and B, a constant third option was included in the uncertainty version, labeled as the *status quo* which was identical across all questions. An example of one of the choice questions with uncertainty is provided in figure III-2. A *status quo* option was included in the survey designed with uncertainty, but is absent from the survey with certain outcomes. The rationale is that, in reality, the *status quo* is uncertain and the presentation of a *status quo* option in the uncertainty version is consistent with this fact. To include a certain *status quo* option in the certain version of the survey would have been confusing to respondents as the outcomes could not have been known with certainty prior to making the trip. Thus, to present the most realistic choice descriptions to respondents meant including a *status quo* option in the uncertainty version, but not the certainty survey version. Despite this difference between the two versions of the survey, there is no confound in comparing marginal utilities across the two approaches.[7] In particular, the econometric approach used here explicitly accounts for the effect of a *status quo* by estimating alternative-specific constants for this option relative to non-*status quo* alternatives.[8]

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[7] There are both conceptual and empirical reasons to believe that including a *status quo* option in the uncertainty but not the certainty version should have no effect on estimated marginal utilities. First, conceptually, the multinomial logit rests on the assumption of independence of irrelevant alternatives (IIA). This means that the estimated utility of an option does not depend on the presence or absence of other alternatives. If IIA holds (as it does in these data), removing the *status quo* option has no effect on estimated marginal utilities of the other included (non-alternative specific) attributes. Second, empirically, several studies have confirmed that including "*status quo*" and "none" options have virtually no effect on the marginal utilities of attributes included in other options (e.g., Carlsson et al., 2007). Finally, the empirical results in this article suggest there was no *status quo* bias in the uncertainty version of the survey.

[8] This approach is actually very similar to the many papers published recently combining revealed and stated preferences. Such studies jointly estimate marginal utilities of product attributes across data types (revealed and stated), while allowing the alternative-specific constants to vary by data type (note: many of the stated preference data sources include a *status quo* option, whereas the revealed preference data do not). This is exactly the approach taken here. Marginal utilities of environmental attributes are jointly estimated, while the alternative-specific constants (one of which relates to the *status quo* in the uncertainty version) vary across data types (certainty and uncertainty). Thus, the approach used here is fully consistent with the recommendations of experts such as Louviere et al. (2000) for handling alternative-specific constants (including "none" and "*status quo*" options) when pooling data.

For a typical trip to Tenkiller Lake, which of the following options do you prefer? (Please check only the box below your preferred option.)

Option A	**Option B**	**Option C: Status Quo**
50% chance of algae bloom	10% chance of algae bloom	50% chance of algae bloom
50% chance of water level 8 feet below normal 50% chance of normal water level	100% chance of water level 2 feet below normal 0% chance of normal water level	10% chance of water level 5 feet below normal 90% chance of normal water level
$2 user fee	$2 user fee	$0 user fee
☐	☐	☐

Figure III-2. Choice card from survey with uncertainty.

Data were collected through in-person interviews on-site at Tenkiller Ferry Reservoir. Four undergraduate student interviewers with prior experience in conducting outdoor recreation surveys were recruited from Northeastern State University in Tahlequah, Oklahoma. Only recreationists 18 years of age or older were eligible to complete the survey. The interviews were conducted at Army Corps of Engineers camp grounds associated with the lake.[9] Interviewers approached lake visitors and requested they

[9] This means that many of the respondents would likely be campers. Further, since only respondents who were currently at the lake were eligible to be included, the sample may be subject to some avidity bias. However, data were collected over Memorial Day weekend, a time in which those who visit less frequently are more likely to visit. More importantly, this article focuses on comparing elicited preferences across two treatments, certainty and uncertainty. Because the sample characteristics (campers, Memorial Day weekend, etc.) are held constant across treatment, the hypothesis test of interest is unconfounded.

complete a short survey. Upon acceptance, interviewers explained several key issues, such as the detrimental effects of algal blooms, what an algal bloom is, and that the user fee would be charged in addition to fees currently charged for camping and other activities. After completing the four discrete choice questions, participants completed several additional questions about the purpose for their lake visit, knowledge of algal blooms, and socio-demographic information.

Results

Data collection took place on May 27–29, 2006. A total of 239 usable surveys were obtained: 126 in the uncertain outcomes treatment and 113 in the certain outcome treatment. Table III-1 provides descriptive statistics for the sample. On average, participants visited Tenkiller Lake about 22 times in the past year. Most of the participants (59%) were male and had an average age of 39. The characteristics of respondents were very similar across the two treatments; thus, it is unlikely that differences in factors such as income and previous observance of algal blooms could explain observed differences in preferences across treatments. In the total sample, only about 22% reported having actually observed an algal bloom on Tenkiller Lake, while39% had never seen one, and the remaining 39% did not know whether they had ever seen one at the location. However, more avid users of the lake were more likely to be aware of water quality problems (the Pearson correlation coefficient between having seen an algal bloom and the number of trips a respondent took to Tenkiller last year was 0.32).

Table III-1. Summary Statistics of Survey Samples

Variable	Definition	Certainty (n=113)	Uncertainty (n=126)	Full Sample (n=239)
Visit	Visitor days last year	21.00 (32.10)[a]	22.67 (33.80)	21.95 (33.00)
Zipdist	Distance from respondent's zip code to Tenkiller Lake	74.84 (76.45)	60.35 (48.62)	66.16 (61.71)
Age	Respondent's age in years	39.80 (13.30)	38.60 (13.50)	39.15 (13.40)
Gender	1 if respondent is male, 0if female	0.60	0.57	0.59
HHsize	Total number of persons living in household	3.77 (1.80)	3.70 (1.80)	3.74 (1.80)
Grpsize	Total number of persons traveling in the vehicle this trip	3.94 (2.80)	3.45 (1.80)	3.68 (2.30)
Seen	1 if respondent has ever seen an algal bloom, otherwise 0	0.21	0.23	0.22
Nseen	1 if respondent has never seen an algal bloom, otherwise 0	0.42	0.37	0.39
Cfish	1 if respondent fished on current trip, otherwise 0	0.58	0.57	0.58
Atrout	1 if respondent is aware of trout fishing area, otherwise 0	0.55	0.58	0.57
Ftrout	1 if respondent ever fishes trout area, otherwise 0	0.20	0.20	0.20
Ctrout	1 if respondent fished trout on current trip, otherwise 0	0.05	0.09	0.07
Ntrout	Number of trout fishing trips per year	1.05 (3.10)	1.40 (5.60)	1.23 (4.60)
Law	1 if respondent aware of litter lawsuit between AR and OK, otherwise 0	0.65	0.67	0.66
Edu	1 if less than H.S. 2 if H.S. diploma 3 if some college 4 if BS/BA or higher	2.74 (0.84)	2.71 (0.93)	2.73 (0.89)
Inc	Annual household income in US dollars	$53,325.40 ($35,609.88)	$55,696.23 ($41,780.24)	$54,561.47 ($38,884.63)

[a] Numbers in parentheses are standard deviations.

To empirically estimate the models in equations (1)–(3), the error terms— ε_{ij} —were assumed to be distributed iid type I extreme value, which produces the familiar multinomial logit (MNL) model, where the probability of choosing option $j = e^{V_{ij}} / \sum_{y=1}^{J} e^{V_{iy}}$.

Rather than treating the marginal utility of water level as a single constant, γ, as in equations (1)–(3), a more flexible representation is allowed by estimating dummy variables for each water level relative to the 10 ft below normal level, the utility of which has been normalized to zero.

The first column of results in table III-2 reports results of a MNL fit to the choice data over certain outcomes. A likelihood ratio test confirms the overall significance of the regression at the 0.01 level. Results are consistent with expectations. People dislike algal blooms, prefer higher water levels, and dislike fee increases. All parameters are statistically significant except the alternative-specific constant for option A relative to option B and the 8 ft below normal water level relative to the 10 ft below normal level. The next column of results in table III-2 pertains to the MNL fit to the choice data over uncertain outcomes. As an initial investigation, the estimation assumes people weight probabilities linearly: that is, it is assumed people choose the alternative that generated the highest expected utility as shown in equation (2) or in equation (3), with $\pi(P) = P$. A likelihood ratio tests indicates the overall model is significant at the 0.01 level. For this model, the alternative-specific constants are estimated relative to option C — the *status quo* option. That the alterative-specific constants are not significantly different from zero means that there is no *status quo* bias in this application (i.e., differences in attribute levels fully explain people's choices between alternatives). The signs of the other

Table III-2. Preferences for Algal Bloom and Water Level: Multinomial Logit Estimates

Parameter	Parameter Definition	Models			
		Choices over Certain Outcomes[a]	**Choices over Uncertain Outcomes[a]**	**Joint[a]**	**Choices over Uncertain Outcomes[b]**
α_A	Constant A – certain	0.151 (0.107)[c]	-	0.126 (0.096)	-
α_A^{UC}	Constant A – uncertain	-	-0.226 (0.177)	-0.044 (0.139)	0.012 (0.190)
α_B^{UC}	Constant B – uncertain	-	-0.114 (0.181)	0.076 (0.140)	0.115 (0.189)
B	Disutility of algal bloom	-0.736**[d] (0.164)	-1.107** (0.208)	-0.785** (0.174)	-0.930** (0.213)
γ_{normal}	Utility of normal water level	1.560** (0. 237)	0.956* (0.477)	1.354** (0.275)	0.800** (0.288)
γ_{2low}	Utility of water level 2 ft low	1.162** (0.249)	0.614 (0.483)	0.930* (0.225)	0.677* (0.318)
γ_{5low}	Utility of water level 5 ft low	0.799** (0.240)	0.479 (0.519)	0.716* (0.240)	0.449 (0.380)
γ_{8low}	Utility of water level 8 ft low	0.277 (0.229)	-0.762 (0.651)	0.108 (0.185)	-1.054 (0.708)
Λ	Cost/Fee	-0.190** (0.033)	-0.085 (0.028)	-0.123* (0.019)	-0.075** (0.028)
Scale	Scale of error term	-	-	1.150[e] (0.262)	-
Φ	Probability weighting parameter	-	-	-	6.725**[e] (1.188)
Δ	Probability weighting parameter	-	-	-	0.259**[e] (0.183)
N[f]		452	504	956	504
LLF		-257.71	-497.19	-762.29	-493.33

[a] Model assumes linear probability weighting.
[b] Model assumes linear log odds probability weighting.
[c] Numbers in parentheses are standard errors.
[d] One asterisk or two asterisks represent statistical significance at the 0.05 or 0.01 level, respectively.
[e] Significance is evaluated against a null hypothesis of parameter equivalent to 1.
[f] N is the number of choice experiments.

variables are as expected, but utility derived from the 2, 5 and 8 ft below normal water levels are not statistically different than that derived from the 10 ft below normal level.

At this point, one might be tempted to compare the coefficient estimates across the first and second columns of results; however, in discrete choice models the estimated parameters are confounded with the error variance. To determine whether the preference parameters from the two models are significantly different from each other, one must control for differences in variance across the two treatments (Swait and Louviere, 1993). To test whether the change in treatment truly caused a shift in preferences (and not just a shift in variance) the two data sets were combined for estimation of a joint model, while estimating a separate relative scale parameter.[10] In this case, the scale parameter for the choices over uncertain outcomes was set to one, and the scale parameter for choices over certain outcomes is estimated as an additional free parameter (Louviere et al., 2000).

Table III-2 shows the results of this estimation under the column titled Joint Model. The estimated scale parameter is 1.15. Because the scale is inversely related to the error variance, this implies a higher variance or "noise" in the treatment where choices were made over uncertain outcomes. While greater "noise" is to be expected when people choose over uncertain outcomes due to the higher level of difficulty associated with answering such questions, uncertainty had no significant effect on the scale parameter in this case. In fact, because the estimated scale of the error is not significantly different than one, it is possible to compare parameters directly across the first two columns of results in table III-2. Doing so makes it clear that people were more averse to algal blooms, less sensitive to changes in water level, and were less price-

[10] Alternative specific constants were not pooled because they are estimated relative to different base categories. Thus the test for preference homogeneity across treatments is a test for equality of preferences for algal bloom, lake level, and user-fee only.

sensitive when choosing over uncertain outcomes as compared to choosing over certain outcomes.

The null hypothesis of equivalence of the preferences across the two data sets (controlling for differences in variance) can be tested by comparing the likelihood function in the third column of results in table III-2 with the sum of the likelihood functions in the two prior columns of results (Louviere et al., 2000). In particular, the likelihood ratio test statistic is: −2(−762.29+257.71+497.19)=14.78, which is distributed chi-square with six degrees of freedom. The 95% critical chi-square value with six degrees of freedom is 12.59. Thus, hypothesis of equal preferences is rejected when people answered stated preference questions over certain and uncertain outcomes.

Although the null hypothesis of preference homogeneity across the two treatments can be rejected, it may be possible that the utility for final outcomes (algal bloomand water level) are identical, but that non-linear probability weighting causes a distortion in estimated parameters. To investigate this issue, people are assumed to evaluate uncertain outcomes as in equation (3) utilizing the following weighting function:

(4) $$\pi(P) = \frac{\delta P^{\phi}}{\delta P^{\phi} + (1-P)^{\phi}}$$

where π is the decision weight, *P* is the probability of an algal bloom or particular water level, and δ and ϕ are parameters relating to the shape of the probability weighting function. This weighting function is the so-called log odds weighting function and has been used by Goldstein and Einhorn (1987), Tversky and Fox (1995), and others. The function is flexible enough to allow under- or over-weighting of low or high probability events and collapses to linear probability weighting if $\delta = 1$ and $\phi = 1$.[11] The last column of results in table III-2 reports the results of this model. Of interest here is whether the inclusion of the two parameters in the probability weighting function significantly increases the maximum value of the likelihood function (note: ϕ and δ were effectively restricted to unity in the second column of results in table III-2). The likelihood ratio test is $-2[493.33 + 497.19] = 7.73 \sim \chi_2^2$. The 95% critical chi-square value with two degrees of freedom is 5.991. The null hypothesis that each of the parameters of the probability weighting function is equal to one can therefore be rejected at the 95% confidence level. This implies that allowing for non-linear probability weighting significantly improves the overall explanatory power of the model.[12]

The relative magnitudes of the two parameters indicate that respondents over-weighted probabilities of likely events and underweighted the probabilities of unlikely events. Figure III-3 shows a plot of the estimated probability weighting function. The graph shows that respondents essentially treated any probability up to about 0.35 as 0 and treated all probabilities greater than about 0.7 as 1, with a high degree of non-linearity in probability weighting between probabilities of 0.4 and 0.7. The shape of this probability function differs from what most researchers investigating choices between monetary prospects have found. The typical finding is that people overweight the probability of an unlikely event and underweight the probability of a likely event (Goldstein and Einhorn, 1987; Tversky and Fox, 1995; Gonzalez and Wu, 1999). However, Humphrey and

[11] The probability weighting functions proposed by Prelec (1998) and Tversky and Kahneman (1992) were also considered. In all cases, the results are similar with regard to the shape of the function and goodness of fit

[12] The null hypothesis of equivalent preferences across the two survey treatments given nonlinear probability weighting was also tested. This hypothesis was rejected at the 0.05 level of significance. The likelihood ratio statistic for this test is 13.96, distributed chi-square with six degrees of freedom.

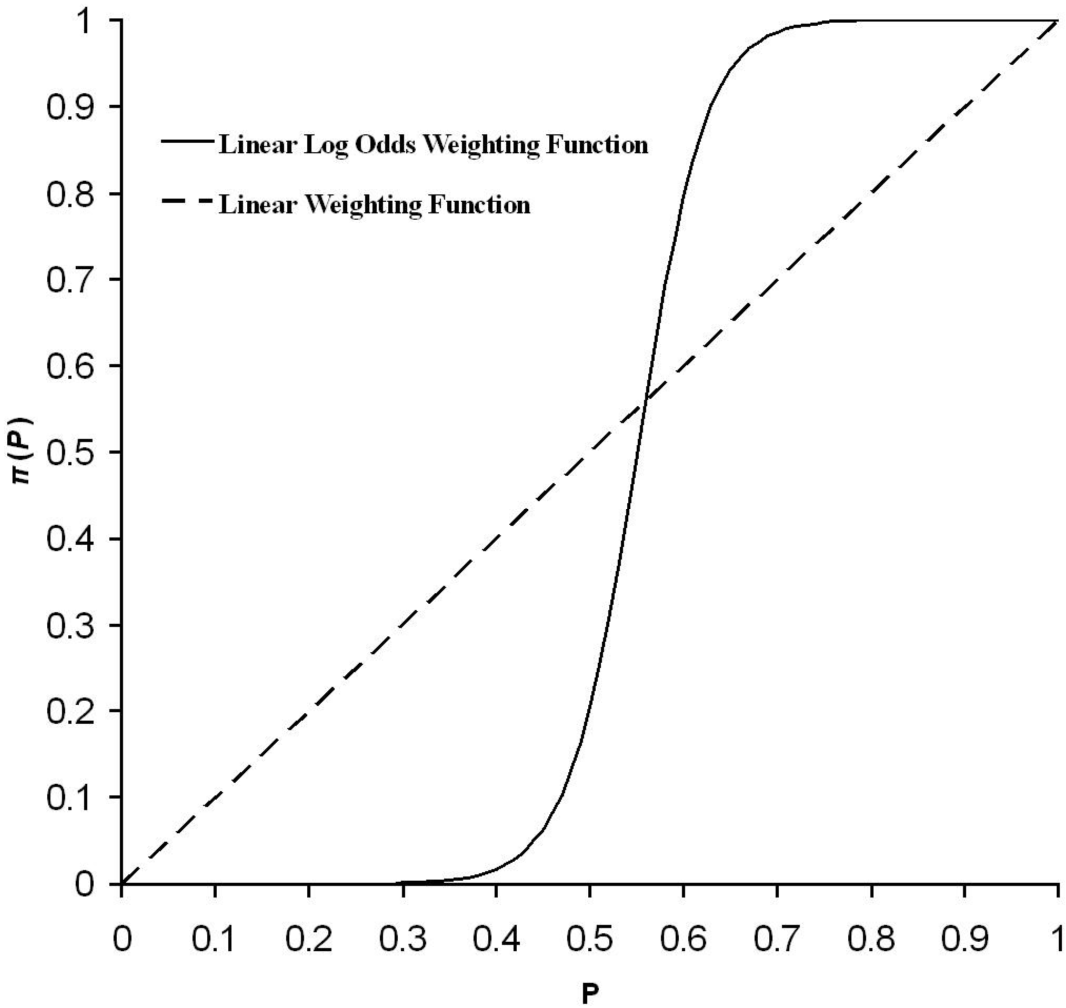

Figure III-3. Estimated probability weighting function.

Verschoor (2004) used the common consequence effect to determine that behavior of rural Ugandans, Indians and Ethiopians in experimental lotteries is best described by an S-shaped probability weighting function, like the one estimated in this paper. They posit that low education levels may have some impact on probability weighting. At this point it is difficult to say with certainty why such a divergent result was found in this analysis, but one possible answer relates to the change in domain. Previous studies involve choices of monetary gambles, but this article investigates how respondents view the probabilities of stochastic events, such as algal blooms and lake levels, which depend in large part upon weather events. Probabilities associated with weather forecasting (or similar events) are representations of epistemic uncertainty (based on prior experience or expertise), whereas probabilities associated with a gamble (e.g., experiments wherein the outcome is decided by a role of the dice) are representations of metaphysical uncertainty (Allhoff, 2005). Indeed, the probability weighting function shown in Fig. 3 is consistent with the way many view weather events. For example, if the meteorologist suggests the chance of rain is 20% tomorrow, most of us are likely to leave the umbrella at home—treating 20% as if it were 0%. Similarly, if the newscaster announces the chance for rain tomorrow is 75%, most of us will pack an umbrella—treating 75% as if it were 100%.

Results in table III-2 show clear differences in responses to choices over certainty and those over uncertainty with regard to fit and functional form; however, the bottom-line is whether the inclusion of uncertainty has any effect of valuation estimates such as WTP. Table III-3 presents WTP estimates for the models shown in table III-2. There is a drastic difference in WTP to avoid an algal bloom between the models under certainty and uncertainty. People were willing to pay three times the amount to eliminate an algal bloom when answering questions over uncertain outcomes as compared to those over certain outcomes. People were also willing to pay more to avoid 10 ft below normal water levels (except for the 8 ft below normal level) when answering questions over uncertain outcomes as compared to those over certain outcomes.

Figure III-4 presents three WTP curves that represent WTP to reduce the probability of an algal bloom from one to any level between one and zero. Note that the vertical intercepts of these WTP curves correspond to the WTP for removal of algal

Table III-3. Willingness-to-Pay Estimates

Willingness-to-Pay for . . .[a]	Choices over Certain Outcomes	Choices over Uncertain Outcomes (assuming linear probability weighting)	Choices over Uncertain Outcomes (with probability weighting function)
removal of algal bloom	$3.87**[b] (0.95)[c]	$13.08** (4.84)	$12.37* (5.32)
normal water level vs. 10 ft. below normal	$8.24** (1.78)	$11.30 (7.23)	$10.64* (5.55)
water level 2 ft. below normal vs. 10 feet below normal	$6.11** (1.46)	$7.26 (6.90)	$9.00 (6.13)
water level 5 ft. below normal vs. 10 feet below normal	$4.20** (1.38)	$5.66 (6.62)	$5.97 (5.54)
water level 8 ft. below normal vs. 10 feet below normal	$1.46 (1.24)	-$9.01 (7.66)	-$14.05 (9.89)

[a] Units are in dollars per visit to Lake Tenkiller.
[b] One asterisk or two asterisks indicate statistical significance at the 0.05 or 0.01 level, respectively.
[c] Numbers in parentheses are standard errors calculated using the delta method.

bloom estimates in table III-3, and that all three curves converge at a WTP of zero where the probability of an algal bloom is one because people are not willing to pay any amount unless the probability is reduced from the reference point of one. The straight solid line and the straight dashed line represent the WTP curves derived from the models without and with uncertainty, respectively. The inverse S-shaped WTP curve is derived from the model under uncertainty with probability weighting, and indicates that because recreationists view a 30% chance of a bloom as essentially equivalent to a 0% chance of a bloom, they are willing to pay approximately the same amount ($12.40 per visit) to reduce the probability of a bloom from 1 to either 0.3 or 0. Similarly, because a 70% chance of a bloom is viewed as equivalent to a 100% chance of a bloom, they are not willing to pay anything for a reduction in the probability of a bloom from 1 to 0.7.

Conclusions

Recreationists at Tenkiller Lake seem to view reducing the probability of an algal bloom as quite an urgent issue relative to regulation of water levels. This urgency is indicated by the relatively high WTP estimates for bloom avoidance given by the models incorporating uncertainty, and also by the fact that approximately 66% of respondents are aware of the lawsuit regarding chicken litter run-off in the Lower Illinois River watershed. The reason for the divergence in risk sensitivity may be due to lower than normal water levels over the past several years, during which Oklahoma has suffered drought conditions. Richardson et al. (1987) suggest that familiarity with an outcome may desensitize individuals to the risk of its occurrence. Water levels have been as low as low as 10 or 8 ft below normal for weeks at a time during late summer and fall at Tenkiller Lake, but the level was at normal pool on the day of the survey. Under such circumstances, lake users are likely to redefine what constitutes an acceptable outcome. On the other hand, algal blooms are relatively less common, and are currently surrounded by a good bit of legal controversy in the region. This risk of algal blooms, therefore, may be viewed by the general public as less acceptable.

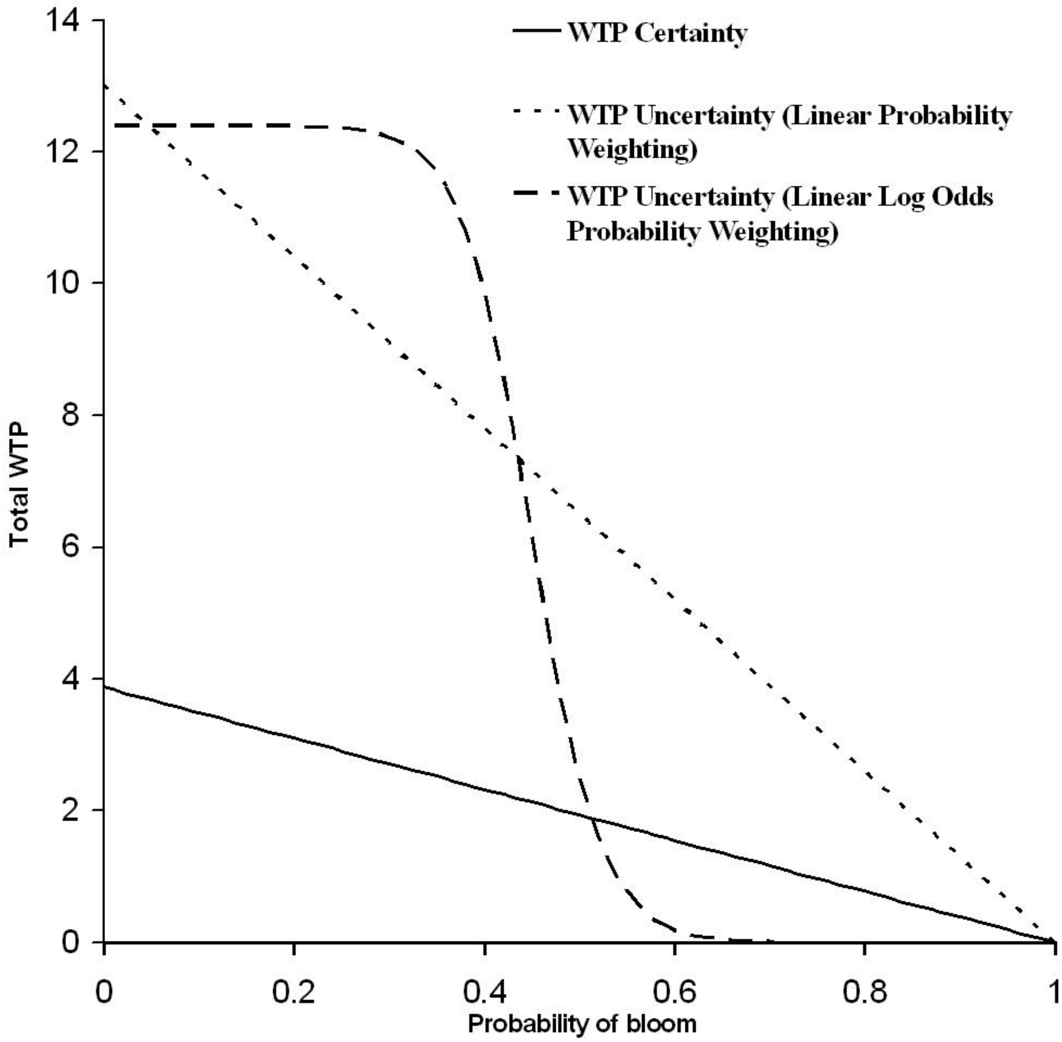

Figure III-4. Willingness-to-pay to reduce the probability of an algal bloom.

This article provides evidence to show that inclusion of risk in the modeling of consumer preferences for environmental goods significantly affects the results of stated choice models. Generally, recreationists show greater WTP when the estimate includes abatement of uncertainty of outcomes. Inclusion of end state uncertainty in the estimation process promotes a more realistic, albeit more complex, choice for each respondent, and may thereby better approximate choice behavior in real situations.

Furthermore, the use of a probability weighting function in the model estimation may better inform the policy making process of stakeholders' WTP for environmental results that are included in the range of feasible policy outcomes, such as average water quality levels. Outcomes described by extreme average water quality levels (very close to 1 or 0 probability of a bloom on any day) are often infeasible and ecologically undesirable; thus, policy-relevant WTP estimates will likely be those that apply to attainable outcomes, or midrange probabilities.

One possible factor contributing to differences between WTP measures elicited under certainty and uncertainty is that when the choice question is more complex, consumers more critically evaluate the tradeoffs between the attributes that vary among the options. Furthermore, the perception of a probabilistic (or risky) outcome may make respondents uncomfortable, such that at some starting levels of risk they are more willing to pay for a marginal change toward a comfortable level of risk. In effect, they ultimately express WTP for a reasonable hope that conditions will be desirable on any particular day they may choose to visit the lake. Lastly, perhaps even in the certain case respondents do not actually believe the outcomes will occur with certainty. That is, they may respond to the choice questions by assigning subjective probabilities to the outcomes in the experiment. To the extent this phenomenon explains the divergence in WTP across treatments, it would lend even more credibility to the notion that practitioners should explicitly incorporate uncertainty into contingent valuation and conjoint questions so the degree of uncertainty can be experimentally manipulated across choice questions, and econometric techniques can be used to determine the extent to which people under- or over-weight probabilities.

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APPENDICES

Appendix A: Institutional Review Board Approval Letter

Oklahoma State University Institutional Review Board

Date:	Thursday, May 18, 2006
IRB Application No	AG0633
Proposal Title:	Valuing Water Quantity and Quality for Recreationists' Expectations of Bluegreen Algal Blooms and Lake Levels in Lake Tenkiller and the Downstream Trout Fishery in the Lower Illinois River
Reviewed and Processed as:	Exempt

Status Recommended by Reviewer(s): Approved Protocol Expires: 5/17/2007

Principal
Investigator(s
Tracy Boyer
312 Ag Hall
Stillwater, OK 74078

The IRB application referenced above has been approved. It is the judgment of the reviewers that the rights and welfare of individuals who may be asked to participate in this study will be respected, and that the research will be conducted in a manner consistent with the IRB requirements as outlined in section 45 CFR 46.

☒ The final versions of any printed recruitment, consent and assent documents bearing the IRB approval stamp are attached to this letter. These are the versions that must be used during the study.

As Principal Investigator, it is your responsibility to do the following:

1. Conduct this study exactly as it has been approved. Any modifications to the research protocol must be submitted with the appropriate signatures for IRB approval.
2. Submit a request for continuation if the study extends beyond the approval period of one calendar year. This continuation must receive IRB review and approval before the research can continue.
3. Report any adverse events to the IRB Chair promptly. Adverse events are those which are unanticipated and impact the subjects during the course of this research; and
4. Notify the IRB office in writing when your research project is complete.

Please note that approved protocols are subject to monitoring by the IRB and that the IRB office has the authority to inspect research records associated with this protocol at any time. If you have questions about the IRB procedures or need any assistance from the Board, please contact Beth McTernan in 415 Whitehurst (phone: 405-744-5700, beth.mcternan@okstate.edu).

Sincerely,

Sue C Jacobs

Sue C. Jacobs, Chair
Institutional Review Board

VITA

David C. Roberts

Candidate for the Degree of

Doctor of Philosophy

Dissertation: PREFERENCES FOR ENVIRONMENTAL QUALITY UNDER UNCERTAINTY AND THE VALUE OF PRECISION NITROGEN APPLICATION

Major Field: Agricultural Economics

Education:

Received Bachelor of Arts degree in Spanish from the University of Tennessee, Knoxville, Tennessee in December of 2003; Awarded Master of Science degree in Agricultural Economics by the University of Tennessee, Knoxville, Tennessee in May of 2006; Completed the requirements for the Degree of Doctor of Philosophy in Agricultural Economics at Oklahoma State University, Stillwater, Oklahoma in July of 2009.

Experience:

Research Assistant in the Department of Agricultural Economics at Oklahoma State University, Stillwater, Oklahoma, 2006-2009; Research Assistant in the Department of Agricultural Economics at the University of Tennessee, Knoxville, Tennessee, 2003-2006.

Professional Memberships:

Agricultural and Applied Economics Association; International Society for Ecological Economics; Northeastern Agricultural Economics Association; Southern Agricultural Economics Association; Western Agricultural Economics Association.

Name: David Carlos Roberts Date of Degree: July, 2009

Institution: Oklahoma State University Location: Stillwater, Oklahoma

Title of Study: PREFERENCES FOR ENVIRONMENTAL QUALITY UNDER UNCERTAINTY AND THE VALUE OF PRECISION NITROGEN APPLICATION

Pages in Study: 164 Candidate for the Degree of Doctor of Philosophy

Major Field: Agricultural Economics

Scope and Method of Study: The first essay in this study models winter wheat producers' choice among potential nitrogen fertilizer application systems that predict nitrogen needs based on optical reflectance data collected from growing plants at different spatial resolutions. Monte Carlo simulation is used to account for the uncertain relationship between optical reflectance data. Expected profits are calculated for each nitrogen application system, and paired differences tests determine which system is most profitable. The second essay addresses winter wheat producers' choice among different field-specific, uniform rate application systems that predict nitrogen needs using optical reflectance data collected from different types of experimental strips. Additionally, Monte Carlo simulation is used to determine the effects of parameter uncertainty on the profit maximization process given the linear response-plateau functional form. Paired differences tests are used to determine the effect of parameter uncertainty on profit maximization and to estimate the relative profitability of the different experimental strip techniques. Essay three determines whether (and how) uncertainty about environmental outcomes influences recreationists' willingness-to-pay for water quality improvements at Lake Tenkiller. On-site interviews were conducted with recreationists at the lake, and multinomial logit estimation is used to model the effect of uncertain outcomes on willingness-to-pay.

Findings and Conclusions: The evidence presented suggests that the nitrogen application strategy expected to be most profitable is to apply 90 kg ha^{-1} each year as anhydrous ammonia, rather than use topdress urea-ammonium nitrate solution, which is much more expensive. Field-level sampling of predictive optical reflectance data is no more profitable than regional sampling. It is also determined that the ramped strip technology is statistically neither more nor less profitable than the nitrogen-rich strip technology. Evidence suggests that, in some cases, accounting for parameter uncertainty improves the predictive accuracy and profitability of optical reflectance-based nitrogen needs predictors. The ramped strip technology is expected to be more profitable when accounting for parameter uncertainty. The Lake Tenkiller study shows that uncertain outcomes affect recreationist willingness-to-pay for water quality, suggesting that uncertainty should be explicitly included in survey instruments for valuation of natural resources and environmental amenities.

ADVISER'S APPROVAL: B. Wade Brorsen